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AD-A026 193

BIOCYBERNETIC CONTROL IN MAN-MACHINE INTERACTION

California University

Prepared for
Office of Naval Research

March 1976

UCLA-ENG-7657
JANUARY 1976

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BIOCYBERNETIC CONTROL IN MAN-MACHINE INTERACTION: SEMI-ANNUAL TECHNICAL REPORT 1975-76 (JULY 1, 1975 to JANUARY 31, 1976)

Sponsored by
Advanced Research Projects Agency
ARPA Order No. 3065

COMPUTER SCIENCE DEPARTMENT

School of Engineering and Applied Science
University of California
Los Angeles

79

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER

2. GOVT ACCESSION NO.

3. RECIPIENT'S CATALOG NUMBER

4. TITLE (and Subtitle)
BIOCYBERNETIC CONTROL IN MAN-MACHINE INTERACTION: SEMI-ANNUAL TECHNICAL REPORT (July 1, 1975 to January 31, 1976)

5. TYPE OF REPORT & PERIOD COVERED
Semi-Annual (July 1, 1975 to January 31, 197[illegible]

6. PERFORMING ORG. REPORT NUMBER

7. AUTHOR(s)
Jacques J. Vidal, Principal Investigator
M.D. Buck, R.J. Hickman, R.H. Olch

8. CONTRACT OR GRANT NUMBER(s)
N00014-76-C-0185

9. PERFORMING ORGANIZATION NAME AND ADDRESS
Department of Computer Science
School of Engineering & Applied Science
University of California, Los Angeles, Calif. 90024

10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
ARPA Order Number: 3065
S.D. State Univ. Foundation Subcontract: 225076

11. CONTROLLING OFFICE NAME AND ADDRESS
San Diego State University Foundation
San Diego State University
San Diego, California 92182

12. REPORT DATE
March 1976

13. NUMBER OF PAGES
79

14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)
Office of Naval Research
1030 East Green Street
Pasadena, California 91105

15. SECURITY CLASS. (of this report)
Unclassified

15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

DISTRIBUTION STATEMENT A
Approved for public release;
Distribution Unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

PRICES SUBJECT TO CHANGE

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)
BIOCYBERNETICS
MAN-MACHINE COMMUNICATION
EEG CODES
VISUAL EVOKED RESPONSES
VISUAL PATTERN STIMULATION

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)
Semi-Annual Report is a progress report of the UCLA Biocybernetics Control project directed toward the evaluation and implementation of man-machine command and control procedures that incorporate neuroelectric signals directly derived from the brain.

This document first reports on the current state of the project. A first milestone has been reached: one such man-machine loop has been operating for several

DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE
S/N 0102 LF 014 6601

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

20. ABSTRACT (Cont.)

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BIOCYBERNETIC CONTROL IN MAN-MACHINE INTERACTION :

SEMI-ANNUAL TECHNICAL REPORT 1975-1976

JULY 1, 1975 to JANUARY 31, 1976

Jacques J. Vidal, Principal Investigator

This research was supported by the
Advanced Research Projects Agency
of the Department of Defense
Under Contract No. N00014-76-C-0185

School of Engineering and Applied Science

University of California

Los Angeles

BIOCYBERNETIC CONTROL IN MAN-MACHINE INTERACTION

SEMI-ANNUAL TECHNICAL REPORT 1975-1976
(July 1, 1975 to January 31, 1976)

Short Title of Work	Biocybernetic Control
ARPA Order Number	3065
Name of Contractor	The Regents of the University of California
Effective Date of Contract	July 1, 1975
Contract Expiration Date	June 30, 1976
Amount of Contract	$110,000
Contract Number	N00014-76-C-0185
Subcontract Number	225076
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I.

NEUROCYBERNETIC CONTROL IN MAN-MACHINE INTERACTION
SEMI-ANNUAL TECHNICAL REPORT 1975-1976
(JULY 1,1975 to JANUARY 31,1976)
UNIVERSITY OF CALIFORNIA AT LOS ANGELES

CONTENTS

ABSTRACT

This Semi Annual Report is a progress report of the UCLA Biocybernetics Control project directed toward the evaluation and implementation of man-machine command and control procedures that incorporate neuroelectric signals directly derived from the brain.

This document first reports on the current state of the project. A first milestone has been reached: one such man-machine loop has been operating for several months at nearly operational performance levels; In the communication protocol of this "MASTER-ROBOT" team, the computer robot executes commands encoded in the master's occipital brain waves (as SINGLE EPOCH VISUAL EVOKED RESPONSES). To send a command the master visually selects the corresponding command symbol from a displayed set. Symbol pattern and color have been used in the command alphabet.

1.1. ORIENTATION

1.1.1 History

The present document is the Semiannual Report, covering the period June 1, 1975 to January 31,1976 for the UCLA Biocybernetics Control in Man -Machine Interaction Project, conducted under ARPA contract to the San Diego State Foundation N00014-76-C-0185 and subcontract # 225076. The long term goals are briefly reviewed and updated below. The ultimate goal of this project is the evaluation and implementation of man-machine command and control procedures that incorporate neuroelectric signals directly derived from the brain.

1.1.2 Neurocybernetics Command and Control Paradigm

The use of bioelectric signals for command or control in the man-machine dialogue can best be discussed under a scenario involving man in the role of operator or "MASTER" (M) communicating with a ROBOT-SYSTEM (RS) The RS can be a sophisticated aircraft, a computerized command system or a number of other man-machine systems. Quite generally it can be said that communication between M and RS takes place through some kind of computer terminal albeit probably one that was designed especially for the task. An aircraft cockpit or the control console of an operation room are essentially computer terminals in the present context. In command and control applications, the master-robot dialogue relate to specific events occuring in the relevant outside WORLD (W). The world in this context consist of the whole environment that affects the man-machine mission. It will normally include the physical manoeuvering space needed by the man-robot team together with other manned or automatic systems operating within the same space in various relations and capacities: (friend or foe, active or passive etc..) Thus W can be a battlefield, a theater of operations, a trajectory in deep space etc... In training situations W is simulated on the computer system, together with the RS itself. The RS assesses W through its sensors i.e. as a quantitative set of numeric or logical variables. The master observes W using visual,acoustic and tactile inputs in the form of a set of displays and messages combined with actual frames of the outside world. Thus his input will include some of the sensor data as shown on his instrument panel (while other sensor data will be kept out in automatic control loops.) Both partners, the man and the machine, therefore share some elements in their input sets but operate on different models of W. These models are central to the decision strategies. The model on which the artificial intelligence of the RS relies is always of relatively low dimension, limited as it is to preassigned classes that are established in terms of the sensor variables V(W). The master also relies on a model of the world but in the form of a mental perception of the global situation that is of immensely larger dimensionality and capable of adaptation to unforeseen circumstances. It rests on sensory capacities and on a memory repertoire at the same time less precise and more adaptive (than those of the RS machinery). It also benefits from the unique capabilities of human perception and intelligence to evaluate input patterns in the complete context of the known situation and to reach quick decisions between perceived alternatives. The efficiency of a man-machine team is tied to the optimization of the division of labor, limiting the human burden to decisions lying at the appropriate level of abstraction while placing as many ancillary functions as possible under automatic control.

1.1.3 The Application Range of the Neurocybernetics Approach

It is useful to recognize the instances that require or justify the search for neurocybernetic channels of communication between master and robot, i.e. the supplemental, remedial or unique advantages gained by adding this capability to the robot system. Four different situations appear to validate the neurocybernetic approach, because of conditions that prevent or limit the use of normal efferent motor channels (such as voice, keyboard, switch, joystick, light-pen etc...) These situations are respectively referred to as Blocking, Dysfunction, Saturation and Latency in terms of the availability of the information that is to be extracted from the neuroelectric signals:

a) Blocking: Information is willfully blocked (stress detector application) or else information is sub-conscious or subliminal (psychotherapy, eidetic imagery,free association, memory probing, face recognition etc...).

b) Saturation: All motor channels are busy (Hi-performance craft in complex combat situation) In that case skeletal output requirements exceed the subject's capacity for real-time control.

c) Dysfunction: Normal motor channels are disabled, either permanently (prosthesis, limb control, sensory substitution etc...) or temporarily (hi-performance aircraft in hi-G pull, spacecraft occupants in low metabolism state, zero-G etc...)

d) Latency: motor channels would be slower, i.e. have longer reaction times than that provided by the neurocybernetic channels (emergency control, selection among set of countermeasures i.e. alternative subroutines as in complex command and control environment).

Of these situations, the three last are clearly relevant to master-robot interaction.

1.2. REVIEW OF RECENT ACCOMPLISHMENTS

1.2.1 Overview

Definite operational success has been reached on the first phase of the program namely the correct recognition and classification of stimulus identity in a small alphabet of possible stimuli, in single epochs of EEG visual evoked response. Stimuli used are flashes either patternless in a set of colors or patterned in one color. Because of the clear differences in codes, patterns and colors are expected to be identifiable separably or in combination although no experiments with combinations have been attempted yet. The experimental strategy and the real-time data processing have been perfected in a succession of experiments and the overall approach is now quite successful with almost any subject. Expected accuracy with random subjects is about 80%. The best subjects operate consistently over 90%

1.2.2 Data Generation and Processing

This level of performance has been obtained by submitting each epoch to a sequence of processing steps namely: (in chronological order)

1.2.2.1 A Priori Artefact Rejection: This step that takes place before actual data processing of the epoch is most important in the general strategy. The frontal pole is continuously monitored for excursions beyond normal range. The real-time experiment monitor aborts data taking when such activity is detected during the half-second preceeding the actual epoch. If it appears during the response itself, (after stimulus) acquisition is completed but the epoch is rejected.

1.2.2.2 Wiener Filtering: This is an optional real-time filtering (based on the covariance matrix derived from the data during training) .Its function is to optimize the signal-to-noise ratio from the standpoint of covariance information. The filter has been the object of a communication at the recent IFIP Conference on Optimization in Nice. Wiener filtering is soon to be combined with time-varying bandpass transformation to enhance fast components at the beginning of the epoch (see Fast EEG components -UCLA-Biocybernetics - Final Report 1975)

1.2.2.3 Stepwise Selection of Best Samples: The ten best samples, from the standpoint of discriminant power, are selected in a stepwise manner, i.e. by order of decreasing power, from the five (electrode)channels using an in-house (BCI) version of the now classical step-wise discriminant procedure used in statistical packages such as the new Biomedical P7M. The BCI program is interactive and designed to run in real-time but otherwise would give identical results. Selection is performed by recursively calculating F-ratios , using a training set containing ten to one hundred responses for each stimulus type.

1.2.2.4 Recursive outlier rejection: A linear decision rule, (Bayesian model, assuming normalcy of distribution and identity of variance for each type) is obtained on the basis of the selected samples. The training set is examined for outliers (i.e. epochs in the training sets that the decision rule misclassifies or fails to classify with an adequate margin) and such epochs can be removed. The program then returns to the stepwise discriminant selection to correct the decision rule. The recursive outlier rejection scheme has not yet been extensively tested and is not yet implemented on-line.

The decision rule is calculated using all non rejected epochs, and applied to subsequent epochs as they are collected; each is then assigned a probability of affiliation to each of the groups.

1.2.2.5 Real-time defaulting: After the initial processing of the training set, i.e. in subsequent epoch-by-epoch classification, the former outlier rejection is replaced by the confinement to a "don't know" category of any epoch that falls beyond a given distance margin for one of the stimulus types.

1.2.2.6 Decision Rule Updating: A recursive "piggy-back" procedure is available as an option for on-line experiments. In that case, blocks of (usually 40) epochs, called epoch strings, are sequentially treated as training sets for the next string. This provides a means by which the decision rule can be tracked as it undergoes changes due to task learning, operant conditioning or any other cause.

1.2.2.7 Neurocybernetic loop: The real-time classification of evoked responses has finally been incorporated in an actual man-machine communication scenario. In this scenario the master is required to run a maze displayed on a graphic terminal. The moving target in the maze (the "mouse" or "mobile") is directed by visually acquiring (i.e. directing the gaze to) one of four visual "keys" that frame the field of operation and thus signal "up", "down", "left" or "right". A diamond shaped, checkerboard pattern, that appears briefly between the keys, produces the evoked response, with the encoded information.

Each stimulus type, as soon as it has been identified in the (occipital) EEG response causes the system to implement the move; thus each successful move constitutes reward. The resulting operant conditioning scheme is therefore directed to the quality or accuracy of the classification in a non-specific way. That learning takes place can be seen in the results of successive runs in the piggyback mode. Typically an increase in performance is recorded over the two or three first runs and will stabilize afterward. The nature of that learning is not elucidated yet, but since these experiments clearly deal with "exogenous" components of the evoked response which are presumed to be relatively resistant to operant conditioning procedures, it is reasonable to suggest that the increase in performance is probably due to the avoidance of interfering processes such a muscle artefacts or even the blocking out of interferring mental activity (casual evidence for the latter is found in the verbal reports obtained from the subjects in recounting their perceptions during experiments)

The maze experiments have been the object of a presentation at the recent IEEE Symposium on Man Machine and Cybernetics in San Francisco.

With regard to these experiments and the entire first-phase of the project it is felt that a limit has been reached in the procedure . No radical change in the data processing approach will be necessary to maintain high levels of performance over a large range of similar experimental conditions, and we would venture to say, with acoustic or tactile stimuli as well. The relatively minor changes that are now in the works and in particular the time-varying Wiener filter are expected to add a few percents to the current levels. In addition, new low noise EEG preamps are expected to increase the performance of the subjects whose brain signals were smaller than average, therefore somewhat buried in the instrumentation noise. Present amplifier noise is 1 to 1.5 microvolts peak to peak; the new amplifiers will be better by a factor of five in noise, and 60 db better in common mode noise rejection. Thus the first phase of the project (time-locked visual evoked responses with stimuli that are (easily) subject discriminable and exogenous signatures in the EEG) is to be considered terminated.

1.2.3 Bibliography

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Vidal, J. J., "Neurocybernetics and Man-Machine Communication", 1975 International Conference on Cybernetics and Society, San Francisco, 1975.

Vidal, J. J., and Ronald H. Olch, "On Line Acquisition and Processing of Epoch-Oriented Continuous Data", Current Computer Technology in Neurobiology Workshop I, University of West Virginia, Morgantown, West Virginia, 1975.

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CHAPTER 2

EXPERIMENTAL PARADIGM

2.1 Man-Machine Environment

Man communicates by perceiving his environment and effecting a structured response to it. The structure is reflected in an ordered selective attention toward each particular component of the perception, along with an interactive protocol established for information transfer with his environment. This research examines responses to inputs on the visual and auditory modalities. The responses observed are electrical fluctuations sensed on the surface of the scalp. These signals represent a simple non-interfering scheme to observe the early components of the biocybernetic processes of the human nervous system.

The paradigm to examine and demonstrate man-machine communication has been implemented in the Brain Computer Interface laboratory. (A current description of this facility as it applies to this research is provided in Appendix I.) The paradigm can be visualized through a scenario in which the principal functions are performed by three elements, the man, the machine, and the environment. The following notation and functional interactions provide a description of the role of these elements in the paradigm.

1) Man as master (M) -- the master observes a robot immersed in a world and learns to generate messages, according to constraints imposed by the world, and the robots capacity for understanding, so that the robot responds to the master's goal.

2) The machine as a robot (R) -- the robot learns to interpret messages from the master and behaves according to its awareness of the world and the constraints imposed by the world.

3) The environment as the world (W) -- the world defines the universe of discourse in the communication between master and the robot and constrains their behavior.

2.2 COMMUNICATION AND FEEDBACK CONTROL

Figure 2-1 presents a simplified block diagram of a biofeedback control loop employed in the experiment. The robot and the world are simulated by the computer system and their interaction is displayed to the master, a human subject, by a cathode ray tube (CRT) display. The subject visually observes the robot's behavior as displayed on the CRT, and issues messages to control the robot according to a protocol with the computer system. This computer system simulates the robot and world with a data collector, message classifier, and robot simulator. The data collector and message classifier reflect the world's constraints on the robot's perception and interpretation of the master's

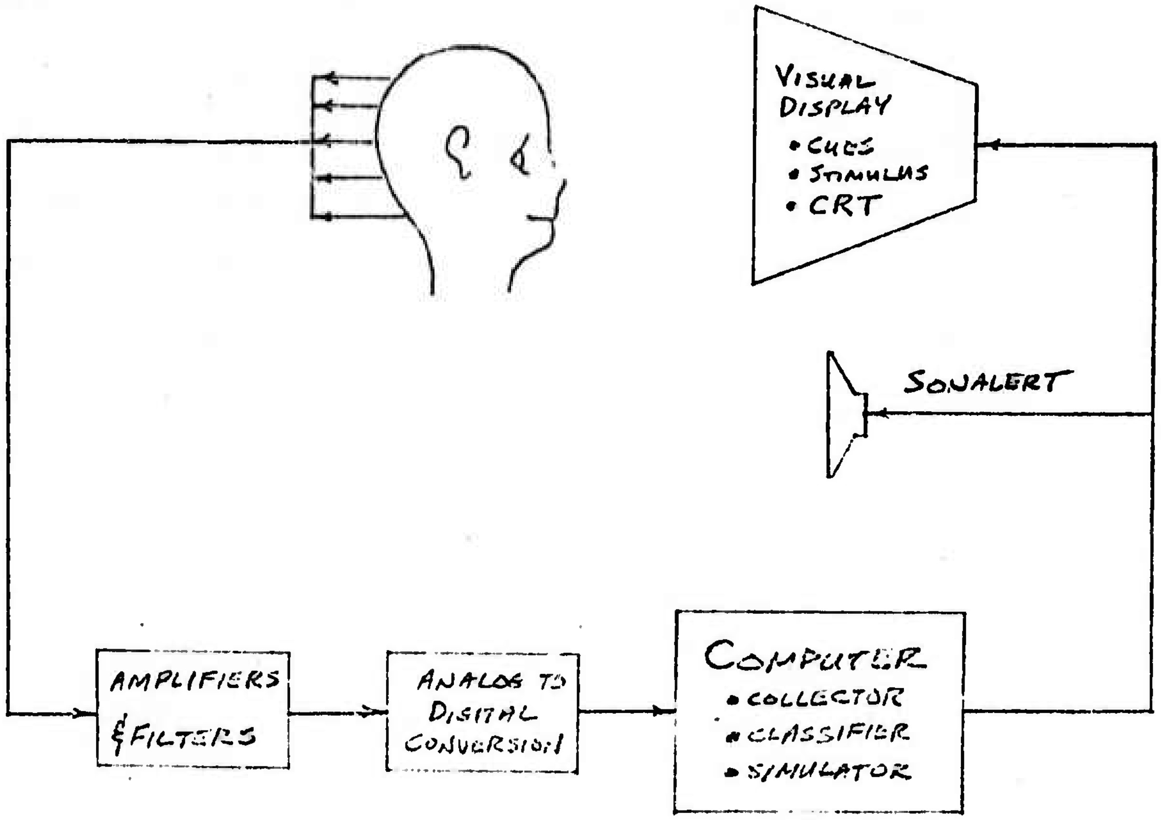

VISUAL
DISPLAY
• CUES
• STIMULUS
• CRT
SONALERT
AMPLIFIERS
& FILTERS
ANALOG TO
DIGITAL
CONVERSION
COMPUTER
• COLLECTOR
• CLASSIFIER
• SIMULATOR

FIGURE 2.1

messages, while the robot simulator implements the decisions made according to the world's constraints on its behavior.

The EEG biofeedback exhibited in this research has different objectives and implementation than previous biofeedback experiments of this type. In this work, biofeedback is an element in a man-machine dialog, rather than simply an indicator of behavior modification. The role of the robot is central to the understanding of this concept of feedback controlled communication. It is through the behavior of the robot that the master is able to determine that his implied commands are getting through, as the behavior of the robot constitutes the feedback signal.

The data processing capability of the Brain Computer Interface laboratory permits analysis of single epochs of multi-channel EEG data, and the techniques developed can identify (on a relatively model-free basis) amplitude, frequency, and phase attributes of the neuroelectric signals involved in the messages transmitted to the robot. This provides a substantial variation and expansion from earlier techniques where simple filters were used to detect cyclic amplitude behavior in EEG signals.

2.3 Current Experimental Implementation

The initial scenario features a (robot) mouse attempting to free itself from confinement in a maze. The robot mouse must move up, down, left, or right along the channels of a maze while attempting to avoid contact with

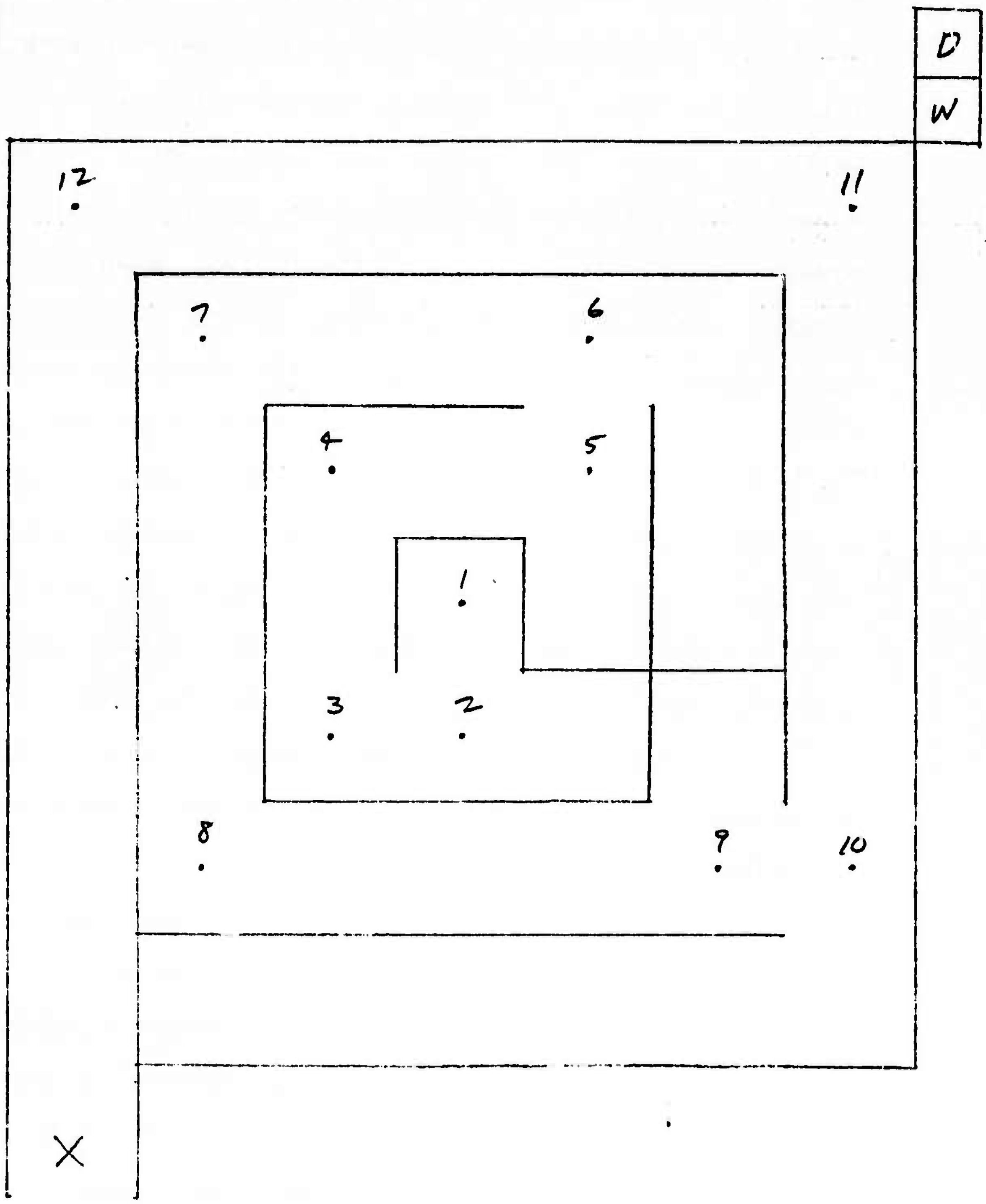
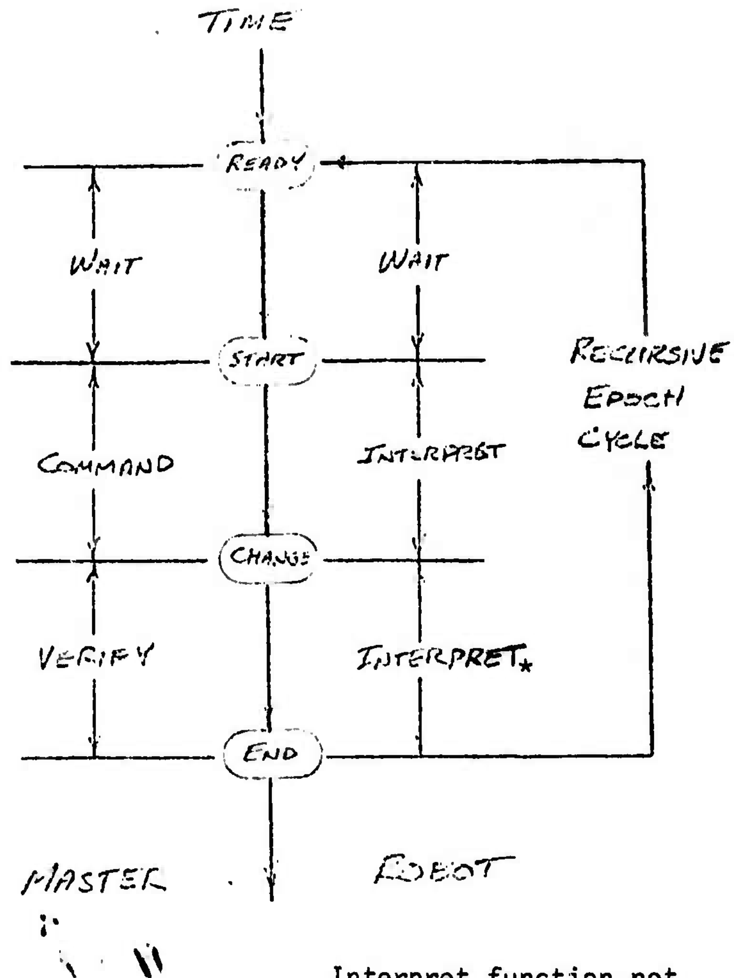


FIGURE 2.2

the walls or unnecessary travel down blind alleys. Figure 2-2 presents a diagram of a maze in which the mouse is initially confined at the center. The shortest path to the exit, in the lower left corner, contains an equal number of moves in each direction. The experimenter can vary the mouse's perception of its world with several options that reflect different levels of intellectual capability in the robot. For instance, the simplest option depicts a dumb mouse that pays no attention to the proximity of adjacant walls, and has no preference to any particular move prior to receiving a message. Other options allow for smarter robots that are aware of adjacant walls or previous moves. In addition to illustrating the value of the robot's intelligence in this approach, these options provide a mechanism for the experimenter to adjust the requirements on the master's message generating capacity. This provision is invaluable in letting the human subject gradually develop his neurocybernetic control capacity.

The major constraints on the communication between master and robot can be illustrated by describing the time sequence of the data collection and command classification processess. Figure 2-3 presents a simplified diagram of the activities and events involved in a single cycle of the communication protocol. This dialog protocol is the basis for the analysis of the data epochs as a time synchronous exchange between the master and the data collector. The initial event of the cycle is a ready cue followed by a wait



* Interpret function not implemented at present

FIGURE 2.3

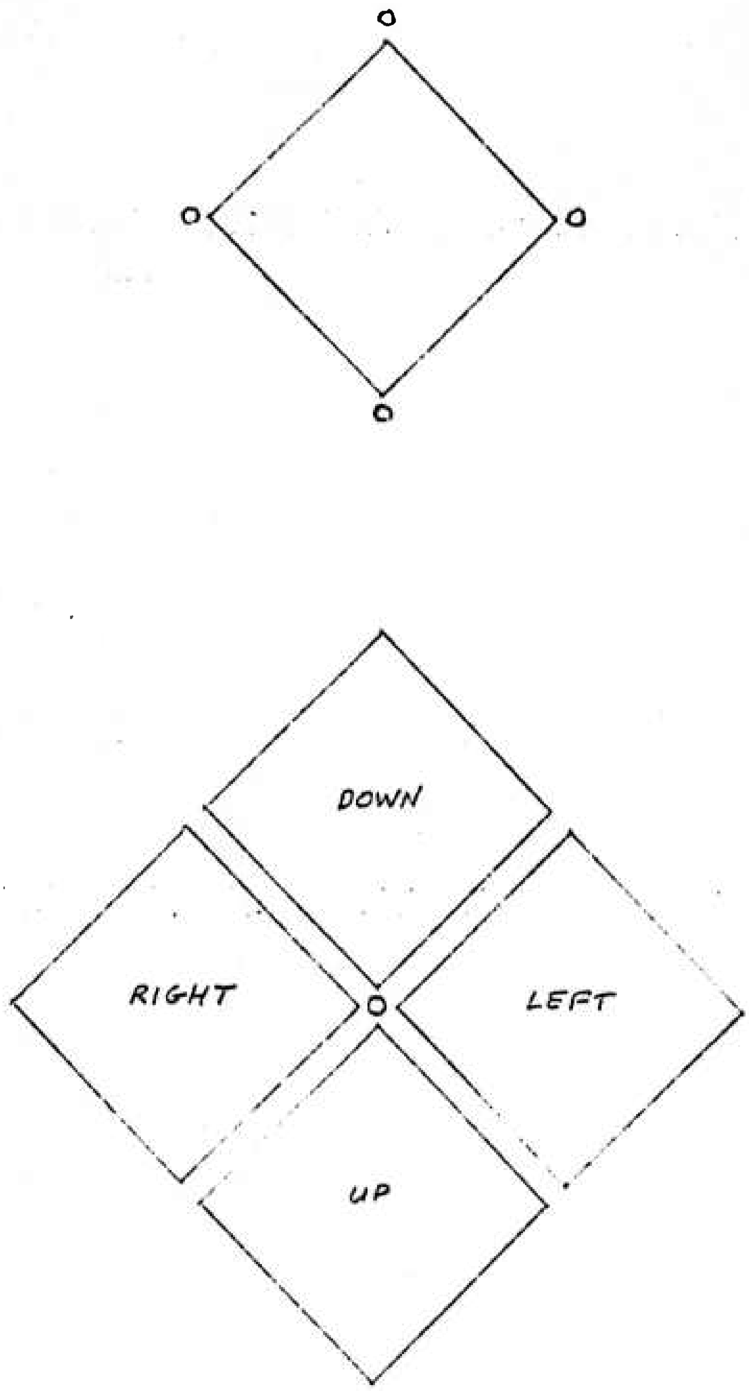


FIGURE 2.4

interval (0.8 sec) to allow the master to select a command. The ready cues include a time coincident beep and LED illumination at one or all vertices of what at stimulus time will appear as a diamond shaped checkerboard pattern superimposed on the CRT display. A strobe light provides the interrupt stimulus, impressing the checkerboard pattern on a portion of the retina, depending on which LED the master directed his gaze during the wait period. Figure 2-4 presents a diagram of the superimposed checkerboard and LED display, and also the form of this pattern as it would appear, given fixation at each vertex. The visual evoked response to the stimulus is transmitted from the master to the robot where it is classified to provide the command. The robot simulator carries out the command and moves the mobile accordingly.

In the subsequent "verify" phase the changing display constitutes a stimulus to the master that confirms or infirms the successful conclusion of the command. The resulting evoked response can then be transmitted to provide a "verify" message that can either cancel the last command or modify the robot's bias in the next cycle.

The nature of scalp electrical activity necessitates a somewhat involved logic to test the properties of the signals during each activity of the cycle. Artifactual signals of apparent random occurance can mask desired signals and must be identified and separated. The artifacts can result from such influences as muscle activity, eye movements or blinks, alpha waves, and sleep spindles. The amplitude of these signals can be several times those of normal responses while the frequencies can vary from 1 - 2 hertz for eye artifacts, 8 - 13 hertz for alpha and spindles, and 50 - 75 for muscle activity.

2.4 Initial Training

Before the master can exercise control of the robot, an initial set of the signals must be analysed. The process of developing a reliable channel of communication involves adaptation of the decoding algorithms implemented by the computer. This initial phase is then complemented by biofeedback as master experiences the effects of changes in his signal generation. On-line real-time data processing techniques are employed to achieve this biofeedback learning.

Thus the sequential procedure begins with an epoch string that involves collection of an initial set of command data messages. This set is analysed to produce a classification function (CF) which is then employed to sequentially classify each command message generated in the next epoch string. This subsequent phase involves data collection, command classification, and activation of the robot based on the results of the classification. The robot action , observed by the master, constitutes the feedback signal and subsequently becomes the stimulus for the verify message. The command messages are then combined with those collected in the first epoch string to produce an updated CF, that incorporates the effects of training and adaptation. Similarly the verify message set from the second epoch string can be analysed to produce a classification function (VF) which will then be employed to subsequently verify command interpretation in the next phase. This process is repeated through several epoch strings with the data collected in each phase refining the CF.

2.5 Data Collection Protocol

The detailed protocol between the master and the on-line data collector is illustrated in Figure 2-5. This diagram presents sequentially the segments of the data collection cycle and includes elements of the controlling logic for data acquisition and artifact handling. This enables the master to sychronize his function with the data collection, classification, display, and storage functions that the data collector performs. The presentation of biofeedback signals to the master provides two types of information. The first is characterized by the cathode ray display provided by the computer and presents the results of the classification of the command signal, i.e., the action of the robot. The second signal is provided by a status panel consisting of a series of colored lights. These lights display the present status of the data collector. A red light indicates the detection of an artifact in the

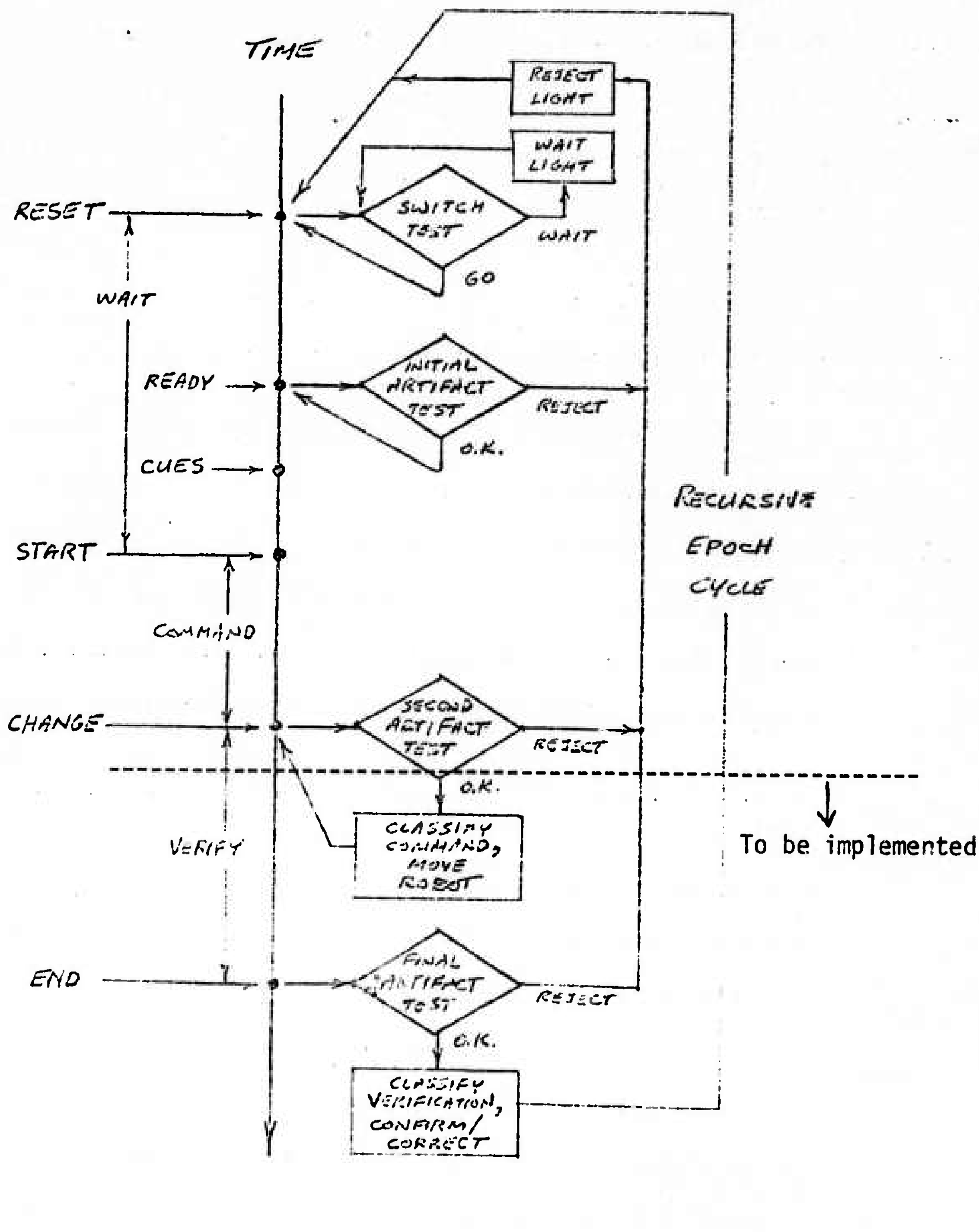


FIGURE 2.5 DETAILED DATA COLLECTION PROTOCOL

data. This signal will remain for a short interval delaying the restart of the collection cycle and eventually allowing the master to alter his behavior in the direction of artifact reduction, while the data collector restarts the real-time data collection segment. Thus the master is trained to produce signals that pass the artifact filter. The design of this artifact detection filter is an important aspect of the experimental paradigm and will be discussed later. The Figure also illustrates the sequence of tests performed to identify artifacts. These tests are performed at the beginning of an epoch, after completion of the command message, and after the verification message. If artifacts are detected at the first two tests, the epoch is abandoned and rescheduled after a short delay with the response of the robot being delayed until the next epoch. An artifact during the verification results in "no decision" regarding the verification. The epoch is not included in future CF generation but the response of the robot is handled according to the options available in the experiment control parameters.

2.6 Biofeedback displays

The main biofeedback signal to the master is provided by the cathode ray tube which displays the world model and the robot's actions in this man-machine paradigm. Figure 2-2 presents an example of such a display. The robot in this example acts on a mobile, "the mouse", displacing its position in a two-dimensional maze. The commands invoke changes in position of the mobile, Namely, move up, move down, move left, or move right. The numbers appearing on the diagram represent decision points: the mobile waits at a decision point for receipt of a command which defines the direction in which it is to proceed. The mobile then moves in this direction at a predetermined rate and halts at the next decision point and waits for the next command from the master.

The alphanumeric characters appearing at the top of the display denote optional modes of behavior. The decision mode restricts the mobile to move only to an adjacant decision point, unless it hits an adjacant wall in which case it returns to the present decision point. The wall mode lets the mobile move until it strikes a wall and then stops at the decision point near the point of impact. This mode involves fewer decision points. Upon reaching the end point (x) the mobile is automatically returned to the starting point.

3. CLASSIFICATION OF BIOCYBERNETIC SIGNALS

Conventional statistical analysis techniques have been employed to classify single epochs of biocybernetic data to one of a set of groups, where each group is associated with a specific command to the machine under control. The principle questions involved in the mathematical treatment of the data epochs includes the choice of a decision logic, a mathematical model of the statistics of the data, and a procedure to efficiently identify the components of the data epoch that provide the most information. Bayes theorem on 'inverse' or posterior probability in combination with stepwise discriminant analysis techniques as described by Dixon form the basis of the approach. The decision logic is based on the Bayesian technique which combines prior information with transmitted information to produce posterior probabilities for group classification of the epoch. The term posterior denotes the fact that the probabilities are determined after incorporating data extracted from the present epoch. The posterior probabilities are unique to the present epoch and represent maximum likelihood estimators of the percentage of these types of epochs that can be found in each group. The statistics of the data epochs are characterized by multivariate normal functions with different means for each group and a covariance matrix that is constant over the groups. The Fisher F-statistic for group separation is the measure employed to evaluate the individual components of the data epochs and a stepwise procedure selects a subset of epoch variables that provide a good, but not necessarily optimal, scheme for extracting the signal components from the data epoch.

The classification of the epoch is accomplished by assigning the epoch to the group with the maximum posterior probability, given that this posterior probability exceeds a specified threshold. An assignment to a group is not made when the maximum posterior probability is less than the threshold. Rather, the epoch is placed in a 'default' category that results in no decision as far as the system is concerned. Epochs placed in the default category may then be excluded from use in determining subsequent discriminant functions. This approach attempts to isolate those epochs that are apparently not representative of the set upon which the present discriminant function was determined. While this approach may appear to favor the 'status quo' it will accept change, as long as the threshold is not too high and the changes are gradual and do not produce a set of posterior probabilities that are all less than the threshold.

The prior information represents what was known before the present epoch was received and incorporation of this prior information into the classification function modifies the interpretation of the commands generated by the subject, and thereby shapes the behavior of the man-machine system. Knowledge of the state of the machine just prior to the time of the epoch is used to weight the chance that each of the possible commands are encoded in the epoch. This effect is characterized as a measure of local context and varies as a function of the state of the machine. Thus the command generating capacity of the subject achieves "apparent" additional dimensions of control in the form of special behavior at particular conditions. The following sections provide a development of the functions used to implement these techniques.

POSTERIOR PROBABILITIES

The posterior probabilities constitute a set of mutually exclusive estimates of the chance that a given epoch should be associated with each of the commands. These probabilities are determined from the Bayes equation where:

$$p(w_i|X) = \frac{p(w_i)\ p(X|w_i)}{p(w_k)\ p(X|w_k)} \tag{3.1}$$

where:

X = a 'd' dimensioned data vector extracted from an epoch.

$p(w_i)$ = prior probability of group w_i.

$p(X|w_i)$ = conditional probability data vector X is from group w_i.

PRIOR PROBABILITIES

The desired command for the machine under control can be highly correlated with the state of the machine at any particular time, and knowledge of this correlation provides the basis for determining the prior probabilities for the Bayes equation.

The prior probabilities are determined for the maze experiment according to several schemes. The first method involves examining the space about the mouse as it reaches different positions in the maze, and assigns low probabilities to commands that would move the mouse directly into an adjacent wall. A second method is designed for the 'wall' mode, where the mouse proceeds down a channel until it strikes a wall. This method determines prior probabilities at each position in the maze such that one of three commands is possible, back-tracking the previous command, or either direction orthogonal to the previous command. Continuing in the same direction as the previous command is not desirable as the previous command will position the mouse at the end of the channel. Back-tracking is weighted according to the probable error in the previous command, while the complement of this error is divided evenly to weight the two orthogonal directions. A final method represents a control comparison and assumes that no information is available, thus the prior probabilities for each command are equal. The following equations define the prior probabilities for the different schemes in the maze paradigm.

1) Smart mouse:

$$p(w_{ij}) = \begin{cases} 0, \text{ if path } i \text{ is obstructed.} \\ \\ 1/n_j, \text{ if path } i \text{ is clear.} \end{cases} \qquad (3.2)$$

where:

j = a position index in the maze.

n_j = the number of clear paths at j.

2) Blind mouse:

$$p(w_i)_j = \begin{cases} 0, & \text{continuing the command from } j-1. \\ [1 - p(w_i|X)_{j-1}], & \text{back-tracking the command at } j-1. \\ p(w_i|X)_{j-1} / 2, & \text{either command orthogonal to } j-1. \end{cases} \quad (3.3)$$

3) Dumb mouse:

$$p(w_i)_j = 1/4, \text{ for all paths at } j. \quad (3.4)$$

It is possible to define many such schemes to temper the results of pattern classifications with prior information. Those just described produce behavior where the mouse exhibits some partial knowledge of the proper command, based on the context of the position in which it finds itself, and the command generating capacity of subject can be selectively enhanced without requiring additional dimensions of control.

CONDITIONAL PROBABILITIES

The conditional probabilities are determined directly from each epoch of biocybernetic data generated by the subject. These probabilities represent measures of the percentage of epochs in each of the groups that are encoded like the data received from the subject in this epoch.

The biccybernetic data extracted from an epoch constitutes a vector which is a sub-set of the samples of EEG voltage fluctuations that comprise a data epoch. The stepwise procedure employed to select the vector components from the data epoch will be described later. The multivariate normal distribution is a convenient candidate for a model of the statistics of the data vector. This distribution function is defined by the following equation.

$$f(X|w_i) = \frac{\exp\left[-0.5\,(X-U_i)^t\,(S_i)^{-1}\,(X-U_i)\right]}{\left[(2\ )^d\,|S_i|\right]^{1/2}} \qquad (3.5)$$

where:

U_i = mean vector from group w_i.

S_i = covariance matrix of vectors in group w_i.

A significant reduction in computational complexity and data processing requirements can be achieved if the covariances of the multivariate distribution functions for each classification group are assumed to be equal. This model with the assumption of equal covariances among groups is not inconsistent with studies of the nature of EEG amplitude statistics. The adequacy of this simplified model in characterizing the nature of the biocybernetic data vector is presented in the discussion. The equations for the conditional probabilities with this simplified model are thus:

$$p(X|w_i) = \frac{\exp[-0.5\,(X-U_i)^t\,S^{-1}\,(X-U_i)]}{[(2\ )^d\,|S|]^{1/2}}\,d|X| \qquad (3.6)$$

Incorporating this model into the posterior probability equations and eliminating terms which are independent of the classification groups, produces the following classification functions.

$$p(w_i|X) = \frac{p(w_i)\,\exp[-0.5\,(X-U_i)^t\,S^{-1}\,(X-U_i)]}{p(w_k)\,\exp[-0.5\,(X-U_k)^t\,S^{-1}\,(X-U_k)]} \qquad (3.7)$$

Expanding the exponentiated term gives:

$$[\cdot] = -0.5\,(X^t S^{-1} X - U_i^t S^{-1} X - X^t S^{-1} U_i + U_i^t S^{-1} U_i) \qquad (3.8)$$

The first term is independent of the classification groups and can be eliminated from the numerator and denominator, and the second and third terms produce identical terms upon expansion, so that the exponentiated term becomes:

$$[\cdot] = -0.5\,(U_i^t S^{-1} U_i) + U_i^t S^{-1} X \qquad (3.9)$$

which can be rewritten as:

$$[\cdot] = a_i + B_i X \qquad (3.10)$$

where:

$$B_i = U_i^t S^{-1}$$

$$a_i = -0.5\,(B_i U_i)$$

and the posterior probabilities reduce to:

$$p(w_i|X) = \frac{p(w_i)\ \exp(a_i + B_i X)}{p(w_k)\ \exp(a_k + B_k X)} \qquad (3.11)$$

SELECTION OF VARIABLES

The first step toward selecting a set of variables from a biocybernetic data epoch is the development of a criteria for measuring the relative performance of the variables in separating the classification groups. The criteria employed in this research is based on the familiar technique of Fisher which examines the ratio of sums of square deviations of the within group means about the grand mean to the sums of square deviations about the within group means. The assumption of equal covariances among the groups provides for the determination of an F-statistic for sets of variables from a population of epochs. The significance of the group separability of the within group means of these variables can then be tested against the chance aspects of the variation of these group means.

The general solution for the set of variables that maximize the separation of the groups involves the solution of a system of linear algebraic equations. These equations are developed from a ratio of variances that determine an F-statistic for an arbitrary sub-set of epoch variables.

The variances for the sub-set of variables are determined from a selection vector and the sums of squares and cross-products matricies of all the variables in the epoch. Two matricies are defined, the first is for the within group means about the population grand mean and the second is for the variables about the appropriate within group means. These matricies are defined as follows:

$$SS_p = (U_k - U_p)^t (U_k - U_p) \qquad (3.12)$$

where:

SS_p = the sums of squares and cross-products matrix for the within group means about the population grand mean.

E = a vector of all variables in an epoch.

U_k = the within group mean of E.

U_p = the population grand mean of E.

Similarly, the within groups sums of squares and cross-products matrix of the data vector is defined by:

$$SS_k = (E - U_k)^t (E - U_k) \tag{3.13}$$

The F-statistic for a particular sub-set of variables can be defined as:

$$F = \frac{(n-g)\, V^t\, SS_p\, V}{(g-1)\, V^t\, SS_k\, V} \tag{3.14}$$

where:

n = number of epochs.

g = number of classification groups.

V = a vector with arbitrary binary elements for selecting variables, 1 to select, 0 to reject.

The selection of the set of epoch variables that maximizes the above F-ratio can be achieved through differentiation of eq. 3.14 with respect to the selection vector V and equating the result to zero, giving:

$$\frac{F}{V} = \frac{2(n-g)\ (V^t SS_k V\ SS_p V - V^t SS_p V\ SS_k V)}{(g-1)\ (V^t SS_k V)^2} = 0 \qquad (3.15)$$

$$= \frac{2(n-g)\ (SS_p V - z\ SS_k V)}{(g-1)\ V^t SS_k V} = 0 \qquad (3.16)$$

where:

$$z = \frac{V^t SS_p V}{V^t SS_k V} \qquad (3.17)$$

The solution of eq. 3.16 is equivalent to the solution of the following system of linear equations:

$$(SS_k^{-1} SS_p - z\ I) V = 0 \qquad (3.18)$$

The stepwise procedure of Efroymson is employed to systematically solve these equations and thereby select the variables from the epoch. This technique also terminates the process when the significance of the contribution of all variables not yet selected falls below a preset level. This procedure tests variables in the selected set (if any) for removal from the set, and then tests variables that have not yet been selected for inclusion in the set. The F-statistics of the individual variables are compared to F-to-remove or F-to-enter levels to determine the course of the stepwise selection. The process is terminated when all variables not yet included in the set possess F-statistics less than the F-to-enter level.

The stepwise technique employs the Gauss elimination method, as described by Orden , for the solution of the simultaneous equations. Initially the variable associated with the largest F-statistic is selected, given that it exceeds the F-to-enter criteria. This variable is eliminated from the matrix by the familiar pivotal transformations where the elements a_{ij} of the succeeding matrix are generated by pivoting the present matrix around the selected variable, denoted here by the subscript kk. The rules for updating the matrix are summarized as follows:

$$a_{ij} = \begin{cases} a_{ij} - a_{ik} a_{kj} / a_{kk} \; ; & \text{if } i \neq k,\ j \neq k \\ a_{kj} / a_{kk} \; ; & \text{if } i = j,\ j \neq k \\ -a_{ik} / a_{kk} \; ; & \text{if } i \neq k,\ j = k \\ 1 / a_{kk} \; ; & \text{if } i = j,\ j = k \end{cases} \tag{3.19}$$

Typically, the variables in the biocybernetic data epochs are correlated over intervals of several adjacent variables, that is neighboring variables tend to exhibit similar amplitudes over a population of epochs from the same classification group. The above pivotal transformations correct the variables in each succeeding matrix for linear correlation with the selected variable so that the correlated nature of biocybernetic variables is systematically handled. However the finite precision of digital processing requires an additional tolerance test prior to the selection of a variable to reduce the possibility of degeneracy when a variable is approximately a linear combination of other variables. Thus if the magnitude of a diagonal element of the matrix in eq. 3.18 is less than a tolerance of 0.01, that variable is not a candidate for selection.

4 EXPERIMENTAL RESULTS

This chapter presents a summary of the results obtained in the laboratory with an initial group of seven subjects on the maze control experiment. The subjects are five females and two males. Individual experimental sessions of about two hours were conducted as described below.

METHODS

Standard Grass silver disc electrodes were applied with electroconductive paste at six locations on the scalp and to both ear-lobes, and electrode impedance was always less than 10,000 ohms. A summary of the electrode sites and channel configurations is presented in Figure 4-1. Channel eight (Fpz - Oz) was used as an artifact detection channel. The logic for detecting an artifact involves counting the amplitude excursions that exceed a threshold in a specified time interval. The analog EEG signals are amplified over the bandwidth of 1.0 to 70.0 Hz., and digitized every 4.0 milliseconds. A data epoch consists of a set of samples collected both before and after a visual stimulus.

Stimuli consist of brief (30 microsec.) flashes of a xenon strobe light (10^7 lux illuminance in a collimated

FIGURE 4.1

TOP: Diagrammatic representation (after Michael & Halliday, 1971) of the relative positions and orientations of hypothetical dipoles connected with the central and peripheral parts of the upper (at 5 o'clock and 8 o'clock) and lower (3 o'clock and 4 o'clock) visual fields. These dipoles are disposed to account for the early (80 to 100 milliseconds to peak) positive voltages seen at electrode Oz (referred to ears) when the lower visual field is flashed (UP command, see Figure 7, Channel 1) and the surface negativity at Oz following upper visual field stimulation (DOWN command, see also Figure 7, Channel 1).

BOTTOM: Topographic projection of left and right hemiretinas onto left and right occipital lobes. This configuration of the brain accounts for the observed large amplitude of the VEP to the RIGHT command in the right occipital electrode, O2-Oz (see Figure 7, Channel 4), and for the large amplitude of the VEP following the LEFT command in the left occipital electrode, O1-Oz (see Figure 7, Channel 3).

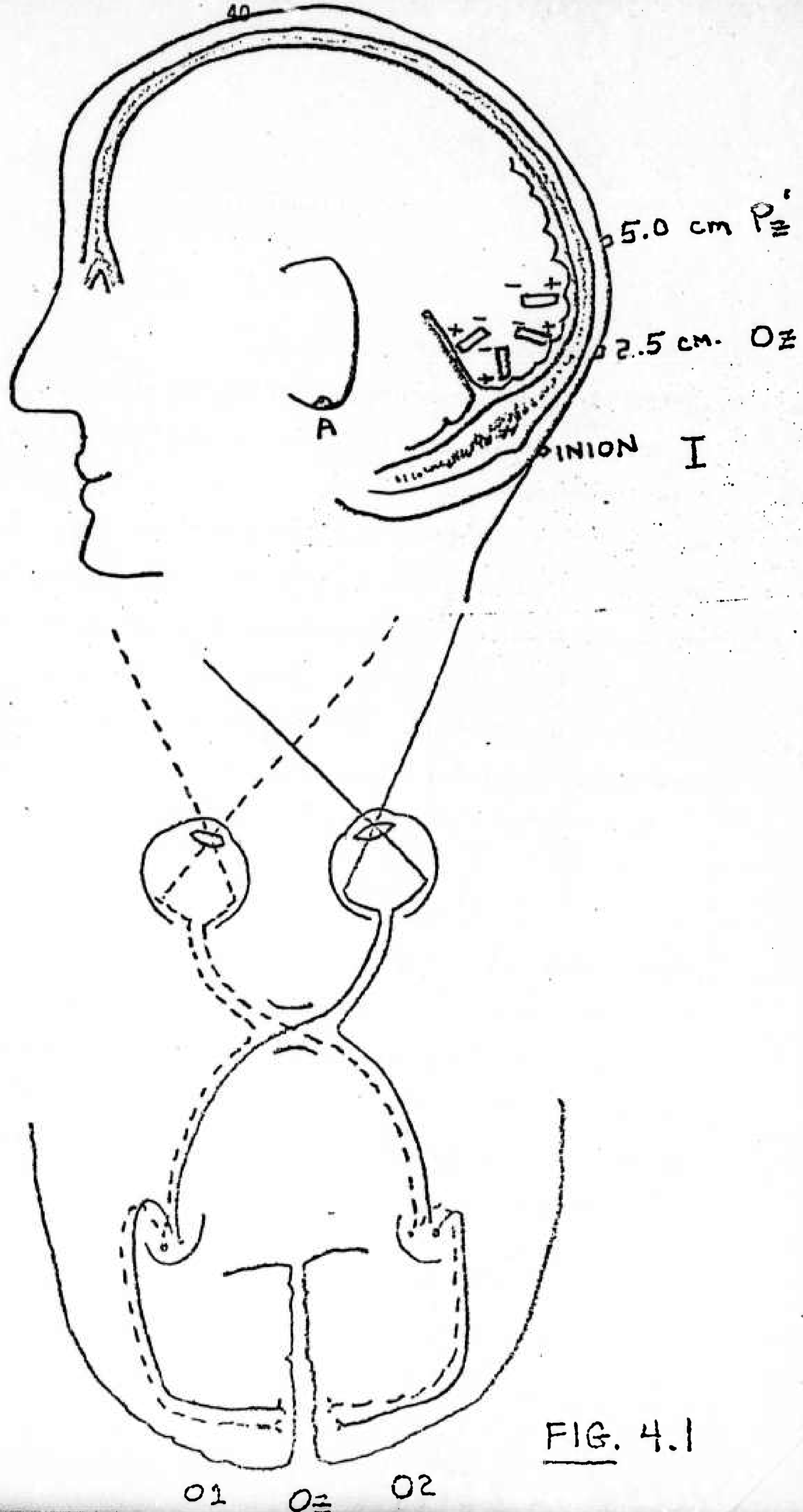


FIG. 4.1

beam) projected through three red gelatin filters, with peak transmission wavelengths of 620 nanometers, and a checkerboard pattern of alternating opaque and clear squares subtending an angle of approximately 77 milliradians with each square subtending 3.5 milliradians. A background light of 10^{-4} lamberts illuminance is also present to allow accomodation to light. All experiments are conducted with the subject seated inside a sound attenuated, electrostatically and radio frequency shielded room.

ANALYSIS

The analysis of the data is performed on-line by the 930 computer. The calculation procedure is implemented in Fortran II programming language and operates on the training set data to generate a sequence of classification functions. These linear functions are used to classify each epoch of the testing sets during which the robot is under control and each epoch constitutes a command to the robot. The performance of the master to robot command channel is evaluated on the basis of a confusion matrix that is generated for each testing set. The rows of the matrix are associated with each of the possible commands to the robot and the columns are associated with each of the possible classifications. Thus there is an additional column in the confusion matrix for the default classification. Examples of the confusion matrix are provided in Tables 4-2 and 4-3.

FIGURE 4.2

SUBJECT SAD7, BCI-SDA CONFUSION MATRICES

These confusion matrices show the performance exhibited by subject SAD7 on an 8 step BCI-SDA analysis. Training set epochs 1 to 280, testing set epochs 281 to 360. Four matrices are calculated using four posteriori probability threshold values.

TESTING CONFUSION MATRIX IEPT = 281 NEPI = 80 IEPS = 1 PT = .8000

SOURCE	PERCENT CORRECT	MUTUAL INFORM.	CLASSIFIED AS UP	DOWN	LEFT	RIGHT	DEFAULT
UP	100.0	1.8203	21.3	.0	.0	.0	2.5
DOWN	100.0	1.6424	.0	23.7	.0	.0	3.7
LEFT	100.0	1.7373	.0	.0	21.3	.0	3.7
RIGHT	100.0	1.8203	.0	.0	.0	21.3	2.5
TOTAL	100.0	1.7506					

TESTING CONFUSION MATRIX IEPT = 281 NEPI = 80 IEPS = 1 PT = .6000

SOURCE	PERCENT CORRECT	MUTUAL INFORM.	CLASSIFIED AS UP	DOWN	LEFT	RIGHT	DEFAULT
UP	100.0	1.9893	22.5	.0	.0	.0	1.2
DOWN	100.0	1.8041	.0	27.5	.0	.0	.0
LEFT	94.7	1.6904	.0	1.2	22.5	.0	1.2
RIGHT	100.0	1.9893	.0	.0	.0	22.5	1.2
TOTAL	98.7	1.8636					

TESTING CONFUSION MATRIX IEPT = 281 NEPI = 80 IEPS = 1 PT = .4000

SOURCE	PERCENT CORRECT	MUTUAL INFORM.	CLASSIFIED AS UP	DOWN	LEFT	RIGHT	DEFAULT
UP	100.0	2.0740	23.7	.0	.0	.0	.0
DOWN	100.0	1.8041	.0	27.5	.0	.0	.0
LEFT	90.0	1.5546	.0	1.2	22.5	1.2	.0
RIGHT	100.0	1.9962	.0	.0	.0	23.7	.0
TOTAL	97.5	1.8515					

TESTING CONFUSION MATRIX IEPT = 281 NEPI = 80 IEPS = 1 PT = .2500

SOURCE	PERCENT CORRECT	MUTUAL INFORM.	CLASSIFIED AS UP	DOWN	LEFT	RIGHT	DEFAULT
UP	100.0	2.0740	23.7	.0	.0	.0	.0
DOWN	100.0	1.8041	.0	27.5	.0	.0	.0
LEFT	90.0	1.5546	.0	1.2	22.5	1.2	.0
RIGHT	100.0	1.9962	.0	.0	.0	23.7	.0
TOTAL	97.5	1.8515					

COMPLETED 8 STEPS OF ANALYSIS

FIG. 4.2

FIGURE 4.3

P7M Classification of SAD6,7,8 &9. 1240 Epochs.

These classification functions resulted from a twenty step BMD P7M run of stepwise discriminant analysis on four experiments using subject SAD. This is a test of stability over a three month period. The jacknifed classification performance simulates a testing set of new data.

CLASSIFICATION FUNCTIONS

VARIABLE	GROUP = UP	DOWN	LEFT	RIGHT
51 X(51)	-0.00013	0.00400	0.00005	0.00067
55 X(55)	0.00467	0.00292	0.00099	0.00196
56 X(56)	-0.00939	0.00011	-0.00539	-0.00514
58 X(58)	-0.02604	-0.00924	-0.01525	-0.01623
70 X(70)	0.00513	0.00182	-0.00286	0.00846
71 X(71)	-0.00061	-0.00089	-0.00195	0.00182
79 X(79)	0.00840	0.00673	0.01256	0.00364
95 X(95)	0.00526	-0.00114	0.00233	0.00302
111 X(111)	-0.00161	-0.00475	-0.00017	-0.00162
121 X(121)	0.01310	-0.00285	0.00606	0.00634
122 X(122)	-0.00621	0.00063	-0.00302	-0.00337
123 X(123)	0.02981	0.00379	0.01269	0.01562
134 X(134)	-0.00622	-0.00957	-0.00912	-0.00383
145 X(145)	-0.01154	-0.00614	-0.00358	-0.01134
157 X(157)	-0.00392	0.00145	-0.00138	0.00223
221 X(221)	-0.00640	0.00172	-0.00181	-0.00028
223 X(223)	-0.00791	0.00405	0.00055	0.00388
234 X(234)	-0.00076	0.00036	0.00179	-0.00330
275 X(275)	0.00251	0.00218	0.00270	-0.00170
284 X(284)	0.00011	0.00134	-0.00227	-0.00040
CONSTANT	-19.05862	-7.25963	-8.93224	-9.88004

CLASSIFICATION MATRIX

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP - UP	DOWN	LEFT	RIGHT
UP	94.6	295	0	1	16
DOWN	93.7	0	296	10	10
LEFT	96.9	0	7	310	3
RIGHT	93.8	9	5	3	274
TOTAL	94.8	304	30[illegible]	324	303

JACKKNIFED CLASSIFICATION

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP - UP	DOWN	LEFT	RIGHT
UP	92.9	290	0	1	21
DOWN	92.4	0	292	11	13
LEFT	96.6	0	8	309	3
RIGHT	92.8	10	5	5	271
TOTAL	93.7	300	306	326	308

FIG. 4.3

The elements of this matrix are generated by recording the history of the classification process on each epoch of a given set. For example, if the correct command is that of the first row and the linear classification function selects the one with the second row, an entry is added to row one, column two. The diagonal elements of the matrix contain the correct classifications and the non-diagonal elements reveal the erronous classifications. Normalizing the entries in the matrix provides estimators of the conditional probabilities of correct command interpretation by the robot and these, in combination with a priori probabilities for the commands, form the basis for measuring the performance of the master to robot communication channel.

PERFORMANCE

MEASUREMENT

$$\text{Mutual Information} = \text{Received Entropy} - \text{Received Equivocation}$$

$$\text{Received Entropy} = \sum_{B} p(b) \ln \left[\frac{1}{p(b)} \right]$$

$$\text{Received Equivocation} = \sum_{A} p(a) \sum_{B} p(b|a) \ln \left[\frac{1}{p(b|a)} \right]$$

$$p(b) = \sum_{A} p(a)\ p(b|a)$$

$$\text{Mutual Information} = \sum_{A} p(a) \sum_{B} p(b|a) \ln \left[\frac{p(b|a)}{\sum_{A} p(a)\ p(b|a)} \right]$$

TABLES 1 to 12

Summaries of the results produced online during the experiments are shown in Tables 1 through 12. The mutual information measure includes the robot in the smart mouse conditions. The maximum is the best 40 epoch performance seen online. Typically, nine recursions were performed, for a total of 360 epochs.

TABLE 1

SUMMARY OF EXPERIMENTAL RESULTS

BEST TESTING PERFORMANCE (DUMB MOUSE)

Performance Measures	Threshold = 0.60			Threshold = 0.25	
	Percent Correct	Percent Default	Mutual Inform.	Percent Correct	Mutual Inform.
Subject - Date					
SAD7 - De23	97.4	5.0	1.83	94.9	1.81
SAD6 - No18	97.1	15.0	1.60	90.0	1.60
JJV2 - Oc19	94.3	12.5	1.62	90.0	1.57
SAD9 - Fe19	94.7	5.0	1.70	90.0	1.51
SAD8 - De30	89.0	8.7	1.42	88.7	1.46
EAH1 - De01	85.2	32.5	1.15	76.9	1.01
MDB2 - Oc14	77.2	10.8	1.00	74.2	1.00
EAC1 - No13	83.3	25.0	1.04	75.0	.96
SAG4 - De22	75.0	40.0	.61	60.5	.78
SAG3 - No20	75.0	30.0	.97	65.0	.69
SDC1 - Oc18	65.7	12.5	.59	67.5	.69

TABLE 2

EXPERIMENTAL RESULTS

SUBJECT: SAC7 DATE: 23DEC75

Performance Measures	Threshold = 0.60			Threshold = 0.25	
	Percent Correct	Percent Default	Mutual Inform.	Percent Correct	Mutual Inform.
Training sets					
Smart mouse					
Averages	96.1	1.9	1.76	95.7	1.76
Std. Dev.	1.4	1.8	.10	1.8	.10
Maximum	98.3	0.	1.89	98.3	1.89
Dumb mouse					
Averages	95.5	1.8	1.68	94.3	1.64
Std. Dev.	.17	.17	.01	.06	.01
Maximum	95.6	1.9	1.69	94.3	1.65
Testing sets					
Smart mouse					
Averages	93.1	6.9	1.67	90.6	1.61
Std. Dev.	5.3	5.5	.22	6.3	.22
Maximum	97.4	5.0	1.81	97.5	1.86
Dumb mouse					
Averages	93.5	3.8	1.69	92.9	1.68
Std. Dev.	5.8	2.1	.21	4.7	.20
Maximum	97.4	5.0	1.83	94.9	1.81

TABLE 3

EXPERIMENTAL RESULTS

SUBJECT: SAL6   DATE: 18NOV75

Performance Measures	Threshold = 0.60 Percent Correct	Threshold = 0.60 Percent Default	Threshold = 0.60 Mutual Inform.	Threshold = 0.25 Percent Correct	Threshold = 0.25 Mutual Inform.
Training sets					
Smart mouse					
Averages	94.7	4.5	1.62	93.1	1.59
Std. Dev.	.37	2.8	.08	1.6	.11
Maximum	95.3	5.0	1.63	95.0	1.76
Dumb mouse					
Averages	94.0	5.8	1.54	91.2	1.47
Std. Dev.	.17	.06	.03	.35	.01
Maximum	94.2	5.7	1.57	91.4	1.48
Testing sets					
Smart mouse					
Averages	90.9	3.8	1.59	88.8	1.51
Std. Dev.	6.2	1.4	.26	6.0	.27
Maximum	97.4	5.0	1.67	95.0	1.74
Dumb mouse					
Averages	88.6	10.0	1.35	83.5	1.34
Std. Dev.	12.9	7.07	.36	9.3	.37
Maximum	97.1	15.0	1.60	90.0	1.60

TABLE 4

EXPERIMENTAL RESULTS

SUBJECT: JJV2 DATE: 19OCT75

Performance Measures	Threshold = 0.60 Percent Correct	Threshold = 0.60 Percent Default	Threshold = 0.60 Mutual Inform.	Threshold = 0.25 Percent Correct	Threshold = 0.25 Mutual Inform.
Training sets					
Smart mouse					
Averages	86.0	24.9	1.00	77.0	.99
Std. Dev.	2.9	15.6	.18	7.0	.11
Maximum	88.0	16.7	1.14	81.5	1.05
Dumb mouse					
Averages	89.1	13.2	1.18	83.5	1.11
Std. Dev.	.14	1.1	.01	.21	.00
Maximum	89.0	12.4	1.19	83.6	1.11
Testing sets					
Smart mouse					
Averages	86.2	8.8	1.39	84.4	1.35
Std. Dev.	10.4	3.2	.36	11.3	.41
Maximum	97.3	7.5	1.81	97.5	1.87
Dumb mouse					
Averages	90.9	16.3	1.40	87.5	1.45
Std. Dev.	4.8	5.3	.31	3.5	.18
Maximum	94.3	12.5	1.62	90.0	1.57

TABLE 5

EXPERIMENTAL RESULTS

SUBJECT: SAL9 DATE: 19FEB76

Performance Measures	Threshold = 0.60 Percent Correct	Threshold = 0.60 Percent Default	Threshold = 0.60 Mutual Inform.	Threshold = 0.25 Percent Correct	Threshold = 0.25 Mutual Inform.
Training sets					
Smart mouse					
Averages	95.1	4.3	1.69	93.0	1.66
Std. Dev.	3.1	2.8	.18	4.0	.20
Maximum	100.0	0.	2.00	100.0	2.00
Dumb mouse					
Averages	94.1	.80	1.68	93.3	1.63
Std. Dev.	--	--	--	--	--
Maximum	94.1	.80	1.68	93.3	1.63
Testing sets					
Smart mouse					
Averages	89.6	3.6	1.56	87.5	1.50
Std. Dev.	3.2	2.5	.11	6.1	.19
Maximum	92.3	2.5	1.65	92.5	1.64
Dumb mouse					
Averages	94.7	5.0	1.70	90.0	1.51
Std. Dev.	--	--	--	--	--
Maximum	94.7	5.0	1.70	90.0	1.51

TABLE 6

EXPERIMENTAL RESULTS

SUBJECT: SAD8   DATE: 30DEC75

Performance Measures	Threshold = 0.60			Threshold = 0.25	
	Percent Correct	Percent Default	Mutual Inform.	Percent Correct	Mutual Inform.
Training sets					
Smart mouse					
Averages	95.5	3.8	1.71	93.5	1.66
Std. Dev.	1.1	2.5	.07	1.8	.11
Maximum	95.0	0.	1.81	95.0	1.81
Dumb mouse					
Averages	94.1	5.9	1.57	92.0	1.54
Std. Dev.	.93	3.2	.05	.46	.02
Maximum	94.7	5.7	1.61	92.5	1.56
Testing sets					
Smart mouse					
Averages	89.1	2.5	1.52	88.1	1.47
Std. Dev.	6.1	2.0	.27	4.7	.22
Maximum	97.4	2.5	1.88	95.0	1.76
Dumb mouse					
Averages	86.6	5.4	1.42	85.4	1.40
Std. Dev.	2.2	3.1	.07	3.1	.12
Maximum	86.6	5.0	1.48	88.7	1.46

TABLE 7

EXPERIMENTAL RESULTS

SUBJECT: EAH1   DATE: 01DEC75

Performance Measures	Threshold = 0.60 Percent Correct	Percent Default	Mutual Inform.	Threshold = 0.25 Percent Correct	Mutual Inform.
Training sets					
Smart mouse					
Averages	88.7	11.9	1.29	84.2	1.24
Std. Dev.	3.4	5.6	.25	4.5	.24
Maximum	94.7	5.0	1.77	92.5	1.65
Dumb mouse					
Averages	88.6	20.6	1.10	80.0	1.00
Std. Dev.	.28	3.2	.04	.57	.00
Maximum	88.6	18.3	1.13	80.4	1.01
Testing sets					
Smart mouse					
Averages	83.4	10.6	1.29	75.8	1.25
Std. Dev.	10.8	6.6	.38	11.5	.28
Maximum	94.6	7.5	1.65	90.0	1.58
Dumb mouse					
Averages	79.1	22.7	.99	72.1	.85
Std. Dev.	5.5	9.8	.14	4.7	.14
Maximum	85.2	32.5	1.15	76.9	1.01

TABLE 8

EXPERIMENTAL RESULTS

SUBJECT: MDE2 DATE: 14OCT75

Performance Measures	Threshold = 0.60			Threshold = 0.25	
	Percent Correct	Percent Default	Mutual Inform.	Percent Correct	Mutual Inform.
Training sets					
Smart mouse					
Averages	95.0	5.5	1.67	92.4	1.58
Std. Dev.	1.4	2.7	.12	1.7	.08
Maximum	96.7	6.3	1.77	93.8	1.66
Dumb mouse					
Averages	91.8	8.9	1.24	86.0	1.08
Std. Dev.	5.0	7.3	.56	9.8	.56
Maximum	96.7	4.7	1.86	93.8	1.73
Testing sets					
Smart mouse					
Averages	89.5	3.2	1.51	89.1	1.47
Std. Dev.	3.5	1.6	.18	4.2	.19
Maximum	93.7	1.6	1.69	93.8	1.69
Dumb mouse					
Averages	65.8	12.5	.66	64.5	.69
Std. Dev.	16.1	2.3	.48	13.8	.44
Maximum	77.2	10.8	1.00	74.2	1.00

TABLE 9

EXPERIMENTAL RESULTS

SUBJECT: EAC1   DATE: 13NOV75

Performance Measures	Threshold = 0.60			Threshold = 0.25	
	Percent Correct	Percent Default	Mutual Inform.	Percent Correct	Mutual Inform.
Training sets					
Smart mouse					
Averages	89.3	17.6	1.24	82.6	1.19
Std. Dev.	5.4	7.3	.36	7.9	.35
Maximum	97.3	7.5	1.82	95.0	1.77
Dumb mouse					
Averages	82.1	28.2	.83	72.4	.83
Std. Dev.	.64	3.1	.01	2.2	.06
Maximum	81.6	26.0	.84	73.9	.87
Testing sets					
Smart mouse					
Averages	60.8	13.8	1.17	74.4	1.04
Std. Dev.	6.4	8.3	.17	3.8	.16
Maximum	65.7	12.5	1.33	77.5	1.18
Dumb mouse					
Averages	69.7	31.3	.78	63.2	.72
Std. Dev.	19.3	8.8	.37	16.8	.34
Maximum	63.3	25.0	1.04	75.0	.96

TABLE 10

EXPERIMENTAL RESULTS

SUBJECT: SAG4 DATE: 22DEC75

Performance Measures	Threshold = 0.60 Percent Correct	Threshold = 0.60 Percent Default	Threshold = 0.60 Mutual Inform.	Threshold = 0.25 Percent Correct	Threshold = 0.25 Mutual Inform.
Training sets					
Smart mouse					
Averages	92.9	10.9	1.47	87.2	1.35
Std. Dev.	1.5	4.2	.15	3.4	.18
Maximum	94.7	5.0	1.72	92.5	1.64
Dumb mouse					
Averages	87.3	17.2	1.10	82.6	1.16
Std. Dev.	1.1	.85	.06	1.6	.06
Maximum	88.0	16.6	1.14	83.7	1.20
Testing sets					
Smart mouse					
Averages	87.5	12.5	1.33	83.1	1.28
Std. Dev.	8.3	4.6	.20	3.2	.14
Maximum	97.0	17.5	1.56	87.5	1.46
Dumb mouse					
Averages	60.8	31.3	.62	59.0	.68
Std. Dev.	7.4	12.4	.01	2.1	.14
Maximum	64.5	27.5	.62	60.5	.78

TABLE 11

EXPERIMENTAL RESULTS

SUBJECT: SAG3 DATE: 20NOV75

Performance Measures	Threshold = 0.60 Percent Correct	Threshold = 0.60 Percent Default	Threshold = 0.60 Mutual Inform.	Threshold = 0.25 Percent Correct	Threshold = 0.25 Mutual Inform.
Training sets					
Smart mouse					
Averages	86.7	18.4	1.10	81.2	1.10
Std. Dev.	3.5	7.2	.25	5.3	.25
Maximum	91.9	7.5	1.54	90.0	1.53
Dumb mouse					
Averages	83.9	21.2	.96	77.8	.95
Std. Dev.	.42	0.	.02	.50	.01
Maximum	84.2	21.2	.97	78.2	.95
Testing sets					
Smart mouse					
Averages	77.1	8.1	1.16	73.8	1.05
Std. Dev.	6.1	6.3	.15	3.2	.09
Maximum	84.8	17.5	1.35	77.5	1.17
Dumb mouse					
Averages	70.8	30.0	.94	61.3	.62
Std. Dev.	2.6	0.	.04	5.3	.11
Maximum	75.0	30.0	.97	65.0	.69

TABLE 12

EXPERIMENTAL RESULTS

SUBJECT: SCC1 DATE: 18OCT75

Performance Measures	Threshold = 0.60 Percent Correct	Percent Default	Mutual Inform.	Threshold = 0.25 Percent Correct	Mutual Inform.
Training sets					
Smart mouse					
Averages	94.4	9.7	1.57	91.0	1.54
Std. Dev.	2.3	2.5	.21	3.8	.21
Maximum	97.3	7.5	1.89	97.5	1.88
Dumb mouse					
Averages	89.9	13.7	1.22	85.0	1.20
Std. Dev.	--	--	--	--	--
Maximum	89.9	13.7	1.22	85.0	1.20
Testing sets					
Smart mouse					
Averages	85.1	3.8	1.48	84.4	1.45
Std. Dev.	7.7	2.5	.21	7.5	.16
Maximum	94.7	5.1	1.77	92.5	1.64
Dumb mouse					
Averages	65.7	12.5	.59	67.5	.69
Std. Dev.	--	--	--	--	--
Maximum	65.7	12.5	.59	67.5	.69

TABLE 13

Subject:SAD7

		CONTRIBUTIONS			
Channel	Time	UP	DOWN	LEFT	RIGHT
OZ-A	236ms	43	8	22	7
PZ-OZ	136	100	6	39	45
O2-OZ	100	41	4	12	42
O2-OZ	140	61	17	5	57
O2-OZ	268	9	2	17	18
I-OZ	132	74	30	34	15

Table 13:
Contributions are shown for each of six variables chosen by a six-step SDA.

CONTRIBUTIONS

In order to ascertain the contribution of each variable to a given group discriminant function (D.F.) the following procedure is adopted, as suggested by Tatsuoka (1971); The coefficients of the variables in the Discriminant Functions are a first approximation to the degree of contribution each variable provides (on the average) to classification of the given group, but these values need correction by a factor (Vi*) which can be obtained in the following manner;
Vi* squared = Vi/d.f., where the Vi are the diagonals of the residuals (variances) in the variance-covariance matrix, d.f. is the number of degrees of freedom associated with the Vi (d.f.=# of epochs-1). Each coefficient in the D.F. is then multiplied by Vi*. Then, for a given experiment, these products are normalized to a maximum of 100 for easy comparison. These Contributions are tabulated in TABLE 13 , 14 , and 15.

TABLE 14

CONTRIBUTIONS

SAD7 10 Step, 8 Var.

Rank	Channel	Time	Commands: UP	DOWN	LEFT	RIGHT
1	Pz-Oz	144	100	5	33	33
4	Pz-Oz	228	75	21	26	23
3	O2-Oz	96	40	1	8	31
5	O2-Oz	156	64	20	17	9
8	I-Oz	80	33	5	2	37
7	I-OZ	132	55	19	22	14
2	I-Oz	140	21	21	9	1
6	I-Oz	224	2	18	7	7

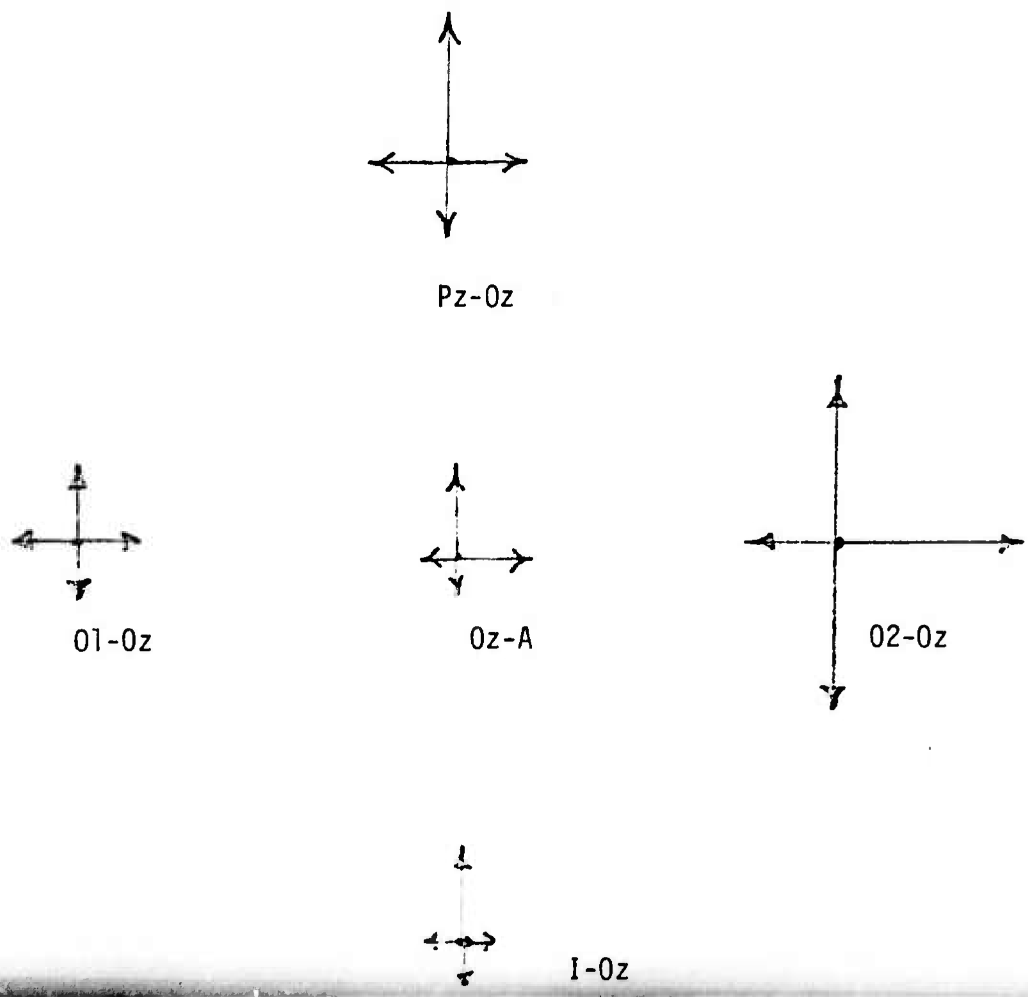
Table 14: Contributions are shown for each of eight variables chosen by a ten-step SDA.

TABLE 15

AVERAGED CONTRIBUTIONS

	UP	DOWN	LEFT	RIGHT
0z-A averages	42	18	18	27
Pz-0z averages	74	44	45	42
01-0z averages	33	29	40	31
02-0z averages	84	89	51	103
I-0z	48	16	20	11

TABLE 15; Average contributions are shown for all subjects, as a function of channel, without respect to time. The cross figures represent the amplitude of the contributions of each channel to the four commands.



TABLES 16 to 18

Shown in Tables 16, 17, and 18 are the levels of classification performance obtained on offline SDA runs with several sizes of training sets, always using the epochs immediately preceeding the 80 epoch testing set.

SAD 6 5 Training Sets

Number of Epochs in Training Set	Train Threshold .6	.25	Test .6	.25	Mutual Info.
40	100%	100%	73.7%	73.7%	.9563
80	96.2	96.2	86.7	83.7	1.2572
120	95	95	92.2	91.2	1.5152
160	97.5	96.9	94.7	93.8	1.6621
200	95.9	95.5	94.8	93.8	1.6625

TABLE 16

SAD 7 Class.Performance vs. Training Set Size

Size (Number of Epochs)	Training %	Test %
40	100.0%	82.5%
80	95.0	86.2
120	94.2	95.0
160	96.2	92.5
200	96.5	92.5
240	95.8	92.5
280	94.3	96.2

TABLE 17

SAD 8 Seven Training Sets: Online Experiment

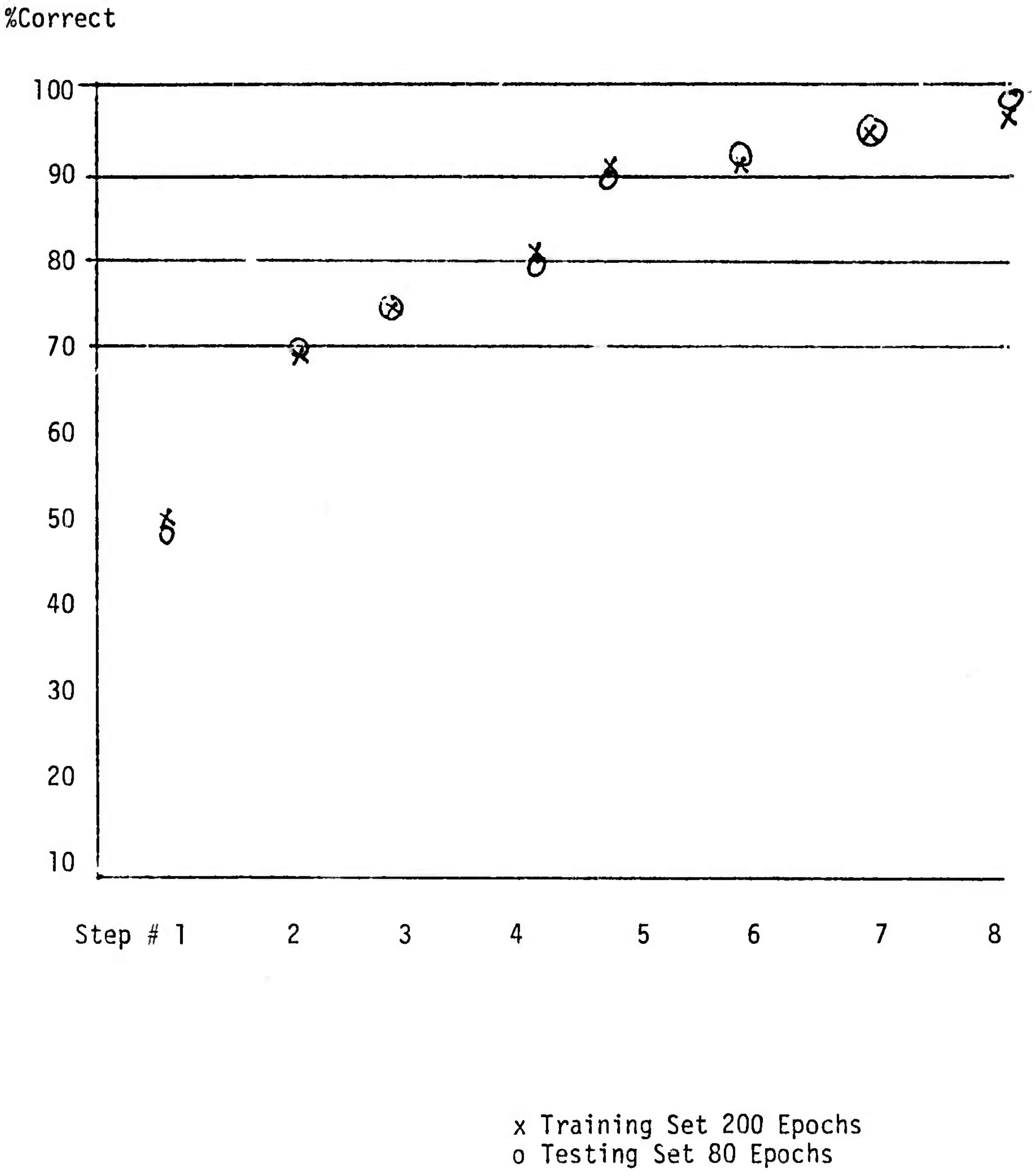
Number of Epochs in Training Set	Train Threshold .6	.25	Test Threshold .6	.25	Mutual Info.
40	100.0	100.0	81.6	80.0	1.1666
80	94.5	90.0	88.0	86.2	1.3234
120	94.7	91.7	87.5	81.3	1.1869
200	93.0	90.5	83.6	78.7	1.1830
240	93.2	92.1	86.5	87.5	1.4252
280	93.4	92.9	89.0	88.7	1.4594

TABLE 18

TABLE 19 shows the classification performance achieved by selecting a more optimal subset of variables than is provided by the wide general window used for most of the online experiments. In order to find a better set of variables, stepwise discriminant analysis was performed repeatedly on the data, taking a narrow time slice of variables across channels per run. When all the time slices were analyzed, a set of usually 60 variables was chosen, and the 40 variables from this list which had the highest F levels were entered into a final SDA run, which gave the performance indicated. Typical training sets were 200 epochs, and testing was performed on 80 epochs.

SUBJECT	MODE	Threshold=.6 % corr	% def	M.I.	Threshold=.25 % corr	M.I.
SAD7	Train	96.5	1.0	1.76	96.0	1.75
	Test	98.7	2.4	1.90	97.5	1.85
SAD6	Train	95.9	2.0	1.69	95.5	1.70
	Test	94.8	3.6	1.68	93.8	1.66
JJV2	Train	93.2	11.5	1.45	90.0	1.43
	Test	88.0	6.1	1.36	87.5	1.37
SAD9	Train	96.9	0.6	1.82	96.2	1.78
	Test	90.7	6.1	1.44	88.7	1.42
SAD8	Train	97.9	4.0	1.80	95.5	1.71
	Test	90.8	4.9	1.53	87.5	1.37
EAH1	Train	88.9	10	1.30	85.5	1.25
	Test	72.2	9.9	0.82	70	.81
MDB2	Train	94.3	11.9	1.50	90.6	1.49
	Test	86.1	9.9	1.20	80.0	1.06
EA01	Train	86.8	24	.99	77.5	.94
	Test	68.4	28.6	.50	61.2	.51
SAG4	Train	89.2	12	1.22	84.5	1.18
	Test	73.1	16.1	.74	67.5	.72
SAG3	Train	87.3	21.5	1.01	80.0	1.05
	Test	68.3	19.9	.50	68.8	.62
SD01	Train	97.4	4.8	1.73	94.4	1.64
	Test	91.5	11.2	1.43	87.5	1.39
AVG	Train	93.1	9.4	1.5	89.6	1.5
	S.D.	4.3	7.9	.3	6.8	.3
	Test	83.9	10.8	1.2	80.9	1.2
	S.D.	11.1	7.9	.5	12.1	.4

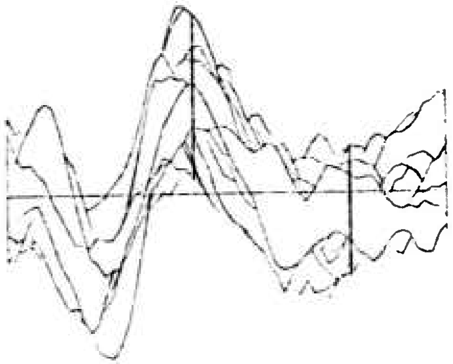
8-Step SDA : SAD 7
200 Epochs



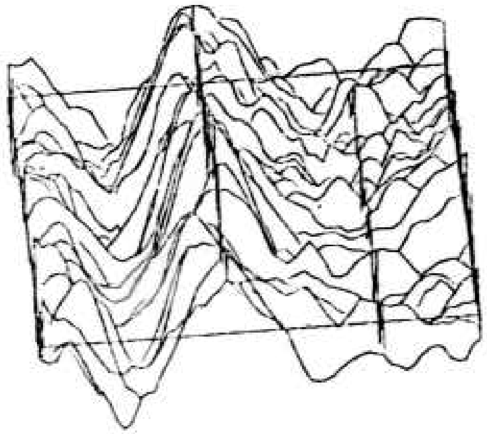
FIGURES 1 to 6

These figures are 3-D plots of single epochs of visual evoked responses from sample 11 (44 msec) on the left to sample 70 (280 msec) on the right. Voltage is on the y axis, and epoch number on the z axis.

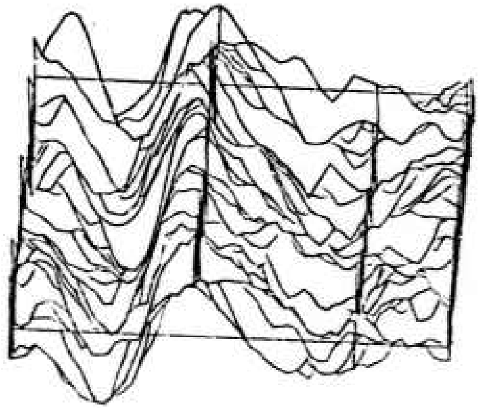
The left top and bottom plots are an end view (z axis perpendicular to the page), with hidden lines, of 50 epochs. The next two plots are top and bottom views. The 8 samples selected by a 10 step SDA run (on one step, a variable was removed) are marked as are the first and last samples.



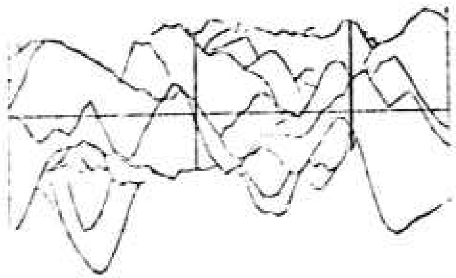
LP EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR:MAZF. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2



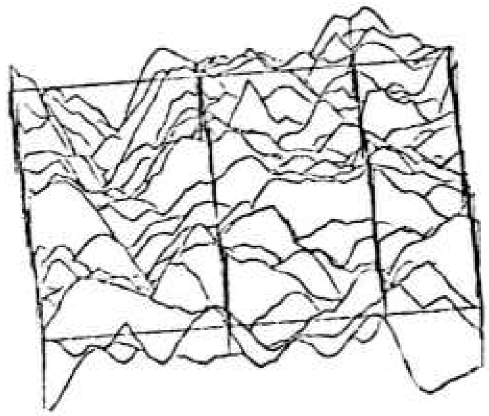
LP EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR:MAZF. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES



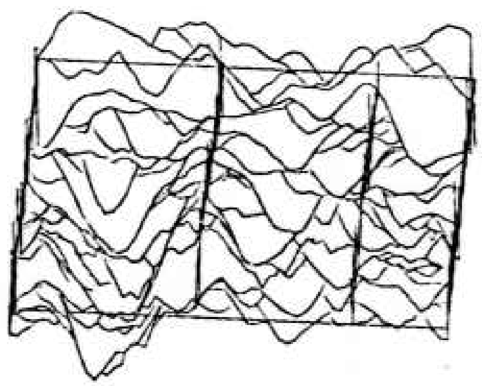
LP EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR:MAZF. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES



DOWN EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR:MAZF. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2



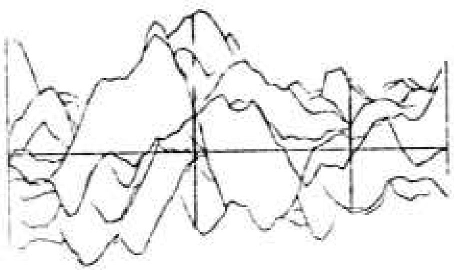
DOWN EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR:MAZF. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES



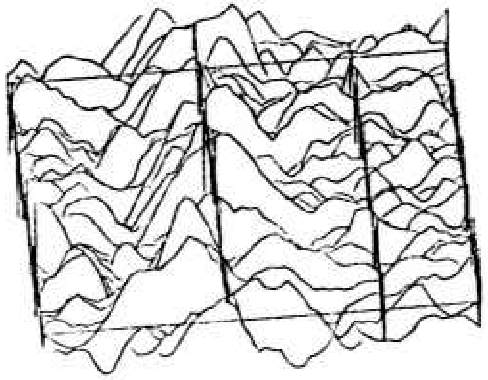
DOWN EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR:MAZF. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES

FIGURE 1

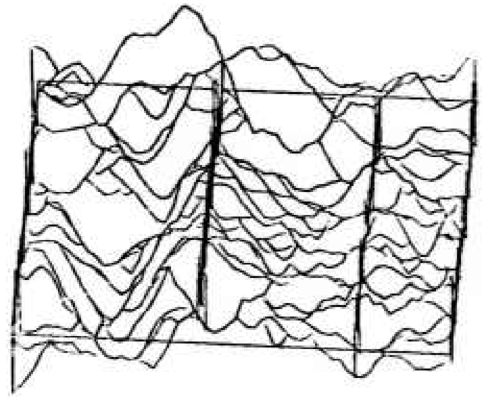
70 B



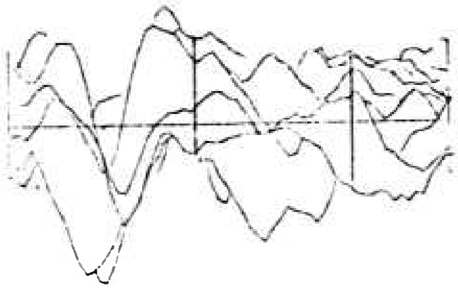
LEFT EPOCHS 1-50. 60 SAMPLES. SA07 OF23
EXPR-MAZE. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2



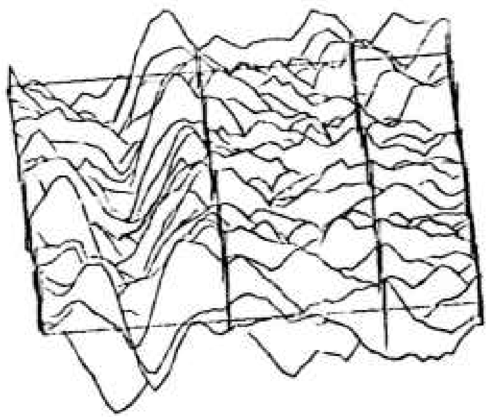
LEFT EPOCHS 1-50. 60 SAMPLES. SA07 OF23
EXPR-MAZE. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES



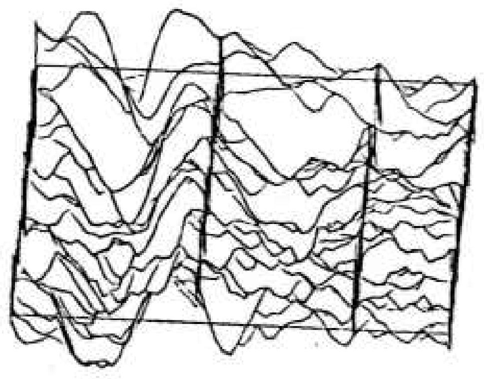
LEFT EPOCHS 1-50. 60 SAMPLES. SA07 OF23
EXPR-MAZE. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES



RIGHT EPOCHS 1-50. 60 SAMPLES. SA07 OF23
EXPR-MAZE. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2

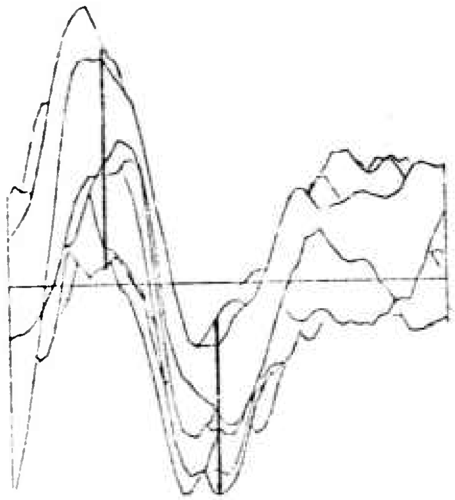


RIGHT EPOCHS 1-50. 60 SAMPLES. SA07 OF23
EXPR-MAZE. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES

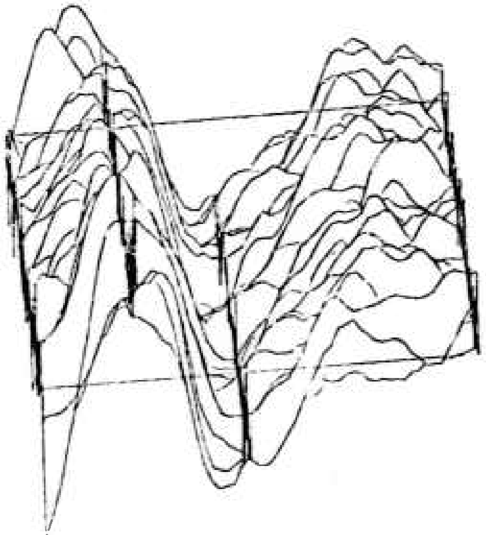


RIGHT EPOCHS 1-50. 60 SAMPLES. SA07 OF23
EXPR-MAZE. CHANNEL 2.PZ-OZ
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES

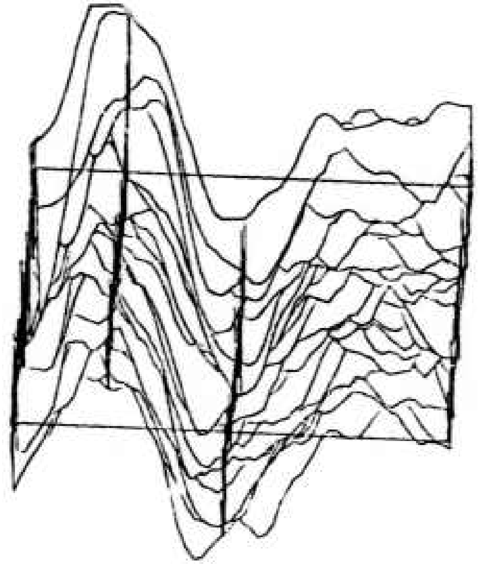
FIGURE 2



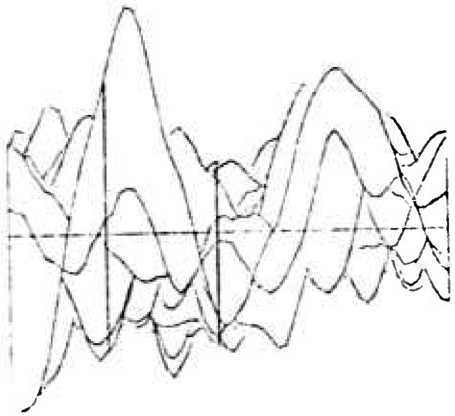
UP EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2



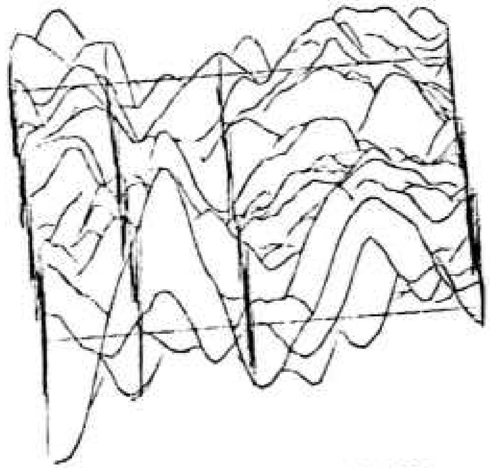
UP EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES



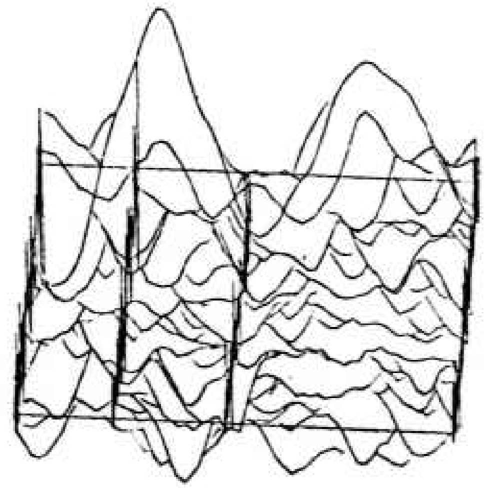
UP EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES



DOWN EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2



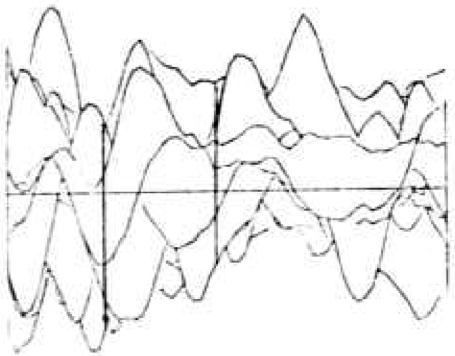
DOWN EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES



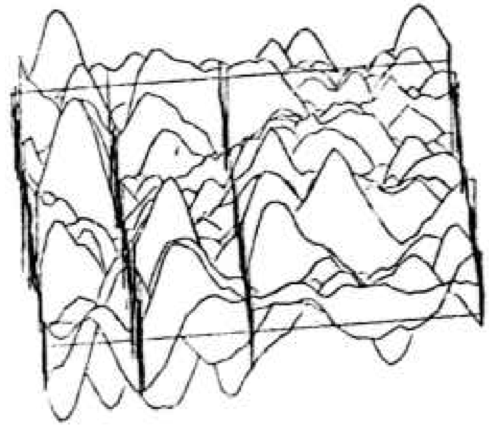
DOWN EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES

FIGURE 3

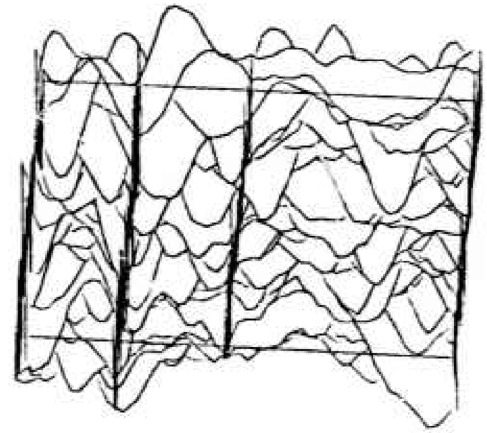
70 D



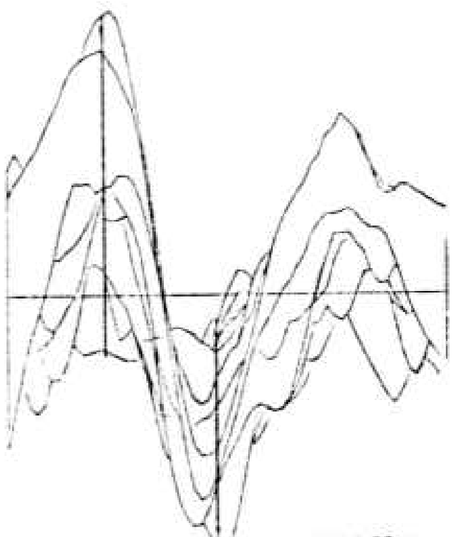
LEFT EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2



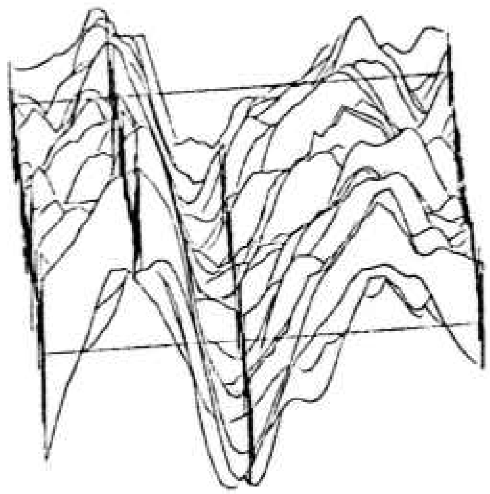
LEFT EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES



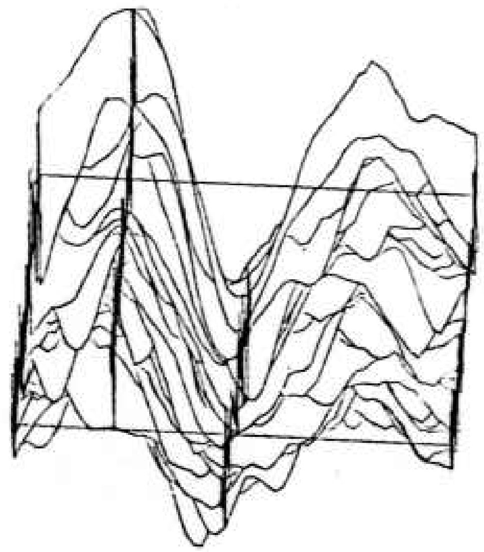
LEFT EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES



RIGHT EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2

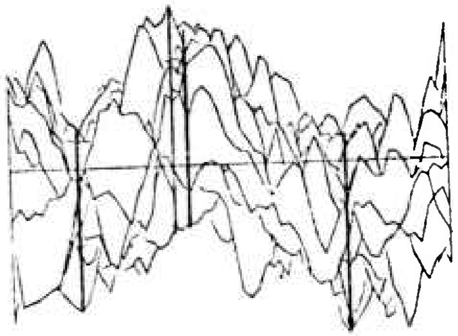


RIGHT EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES

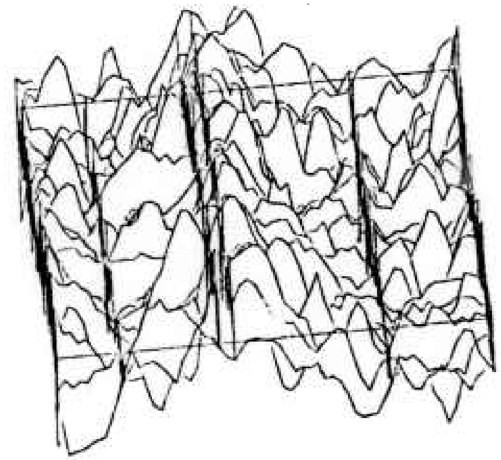


RIGHT EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR-MAZE. CHANNEL 4. 02-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES

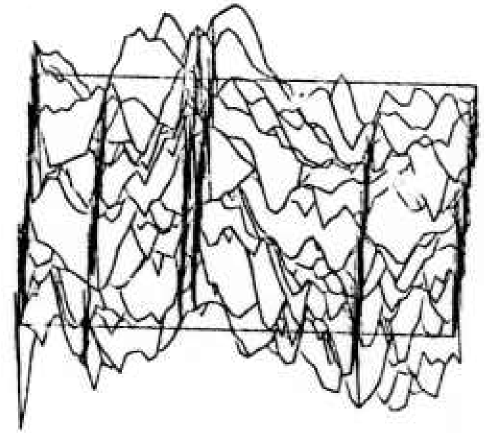
FIGURE 4



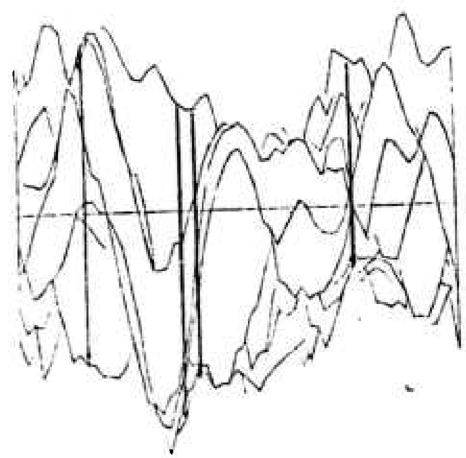
UP EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR MAZE. CHANNEL 5. 1-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2



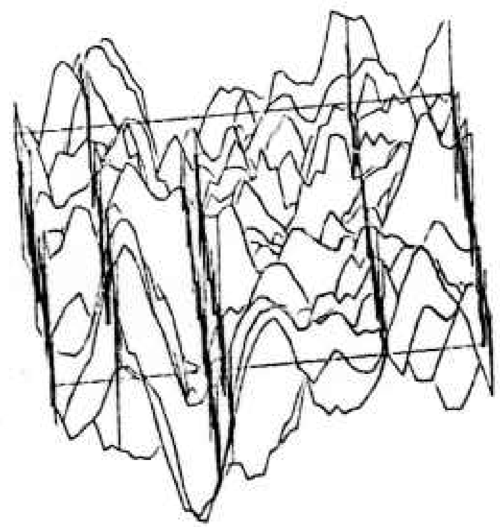
UP EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR MAZE. CHANNEL 5. 1-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES



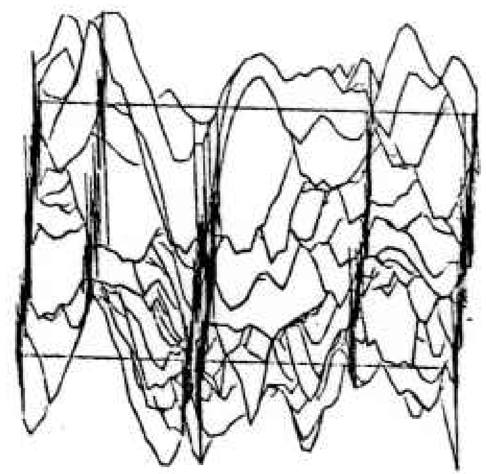
UP EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR MAZE. CHANNEL 5. 1-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES



DOWN EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR MAZE. CHANNEL 5. 1-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2

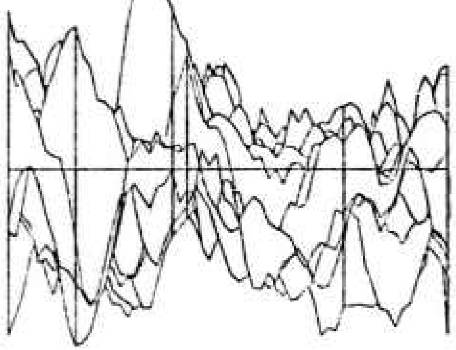


DOWN EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR MAZE. CHANNEL 5. 1-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES

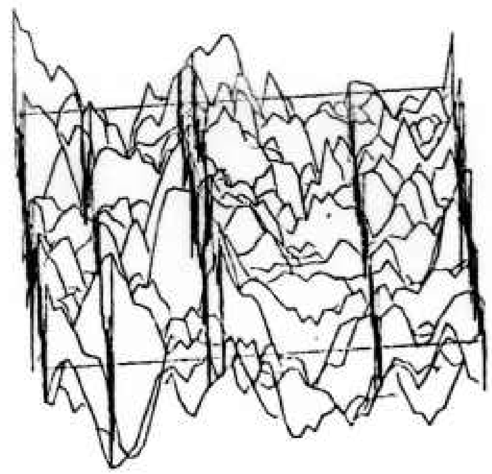


DOWN EPOCHS 1-50. 60 SAMPLES. SAD7 DF23
EXPR MAZE. CHANNEL 5. 1-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES

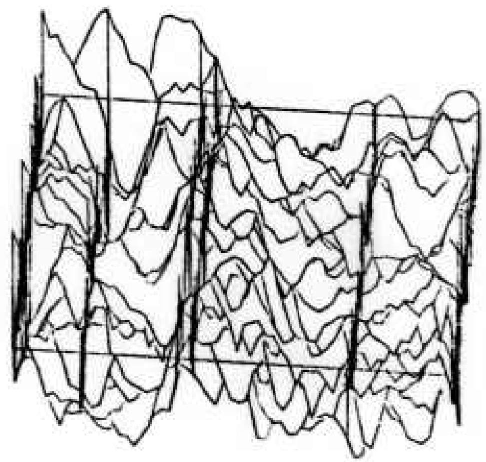
FIGURE 5



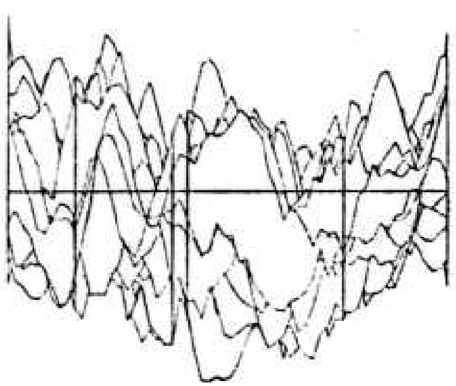
LEFT EPOCHS 1-50. 60 SAMPLES. SAD7 DE23
EXPR=MAZE. CHANNEL 5. 1-07
SELECTED SAMPLES MARKED. SMOOTHED BY 2



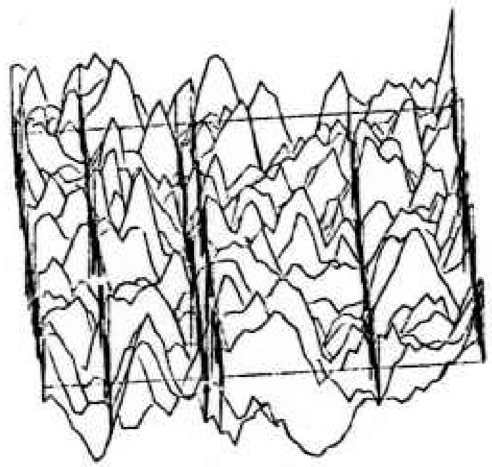
LEFT EPOCHS 1-50. 60 SAMPLES. SAD7 DE23
EXPR=MAZE. CHANNEL 5. 1-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES



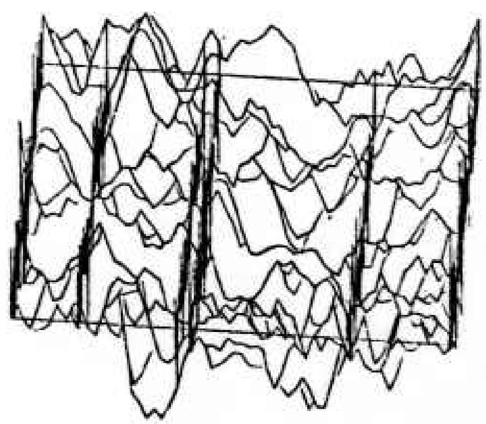
LEFT EPOCHS 1-50. 60 SAMPLES. SAD7 DE23
EXPR=MAZE. CHANNEL 5. 1-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES



RIGHT EPOCHS 1-50. 60 SAMPLES. SAD7 DE23
EXPR=MAZE. CHANNEL 5. 1-07
SELECTED SAMPLES MARKED. SMOOTHED BY 2



RIGHT EPOCHS 1-50. 60 SAMPLES. SAD7 DE23
EXPR=MAZE. CHANNEL 5. 1-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
TOP VIEW. -5 DEGREES BY -45 DEGREES



RIGHT EPOCHS 1-50. 60 SAMPLES. SAD7 DE23
EXPR=MAZE. CHANNEL 5. 1-02
SELECTED SAMPLES MARKED. SMOOTHED BY 2
BOTTOM VIEW. -5 DEGREES BY 45 DEGREES

FIGURE 6

FIGURES 7 to 17

AVERAGES OF VISUAL EVOKED RESPONSES FROM ONLINE EXPERIMENTS

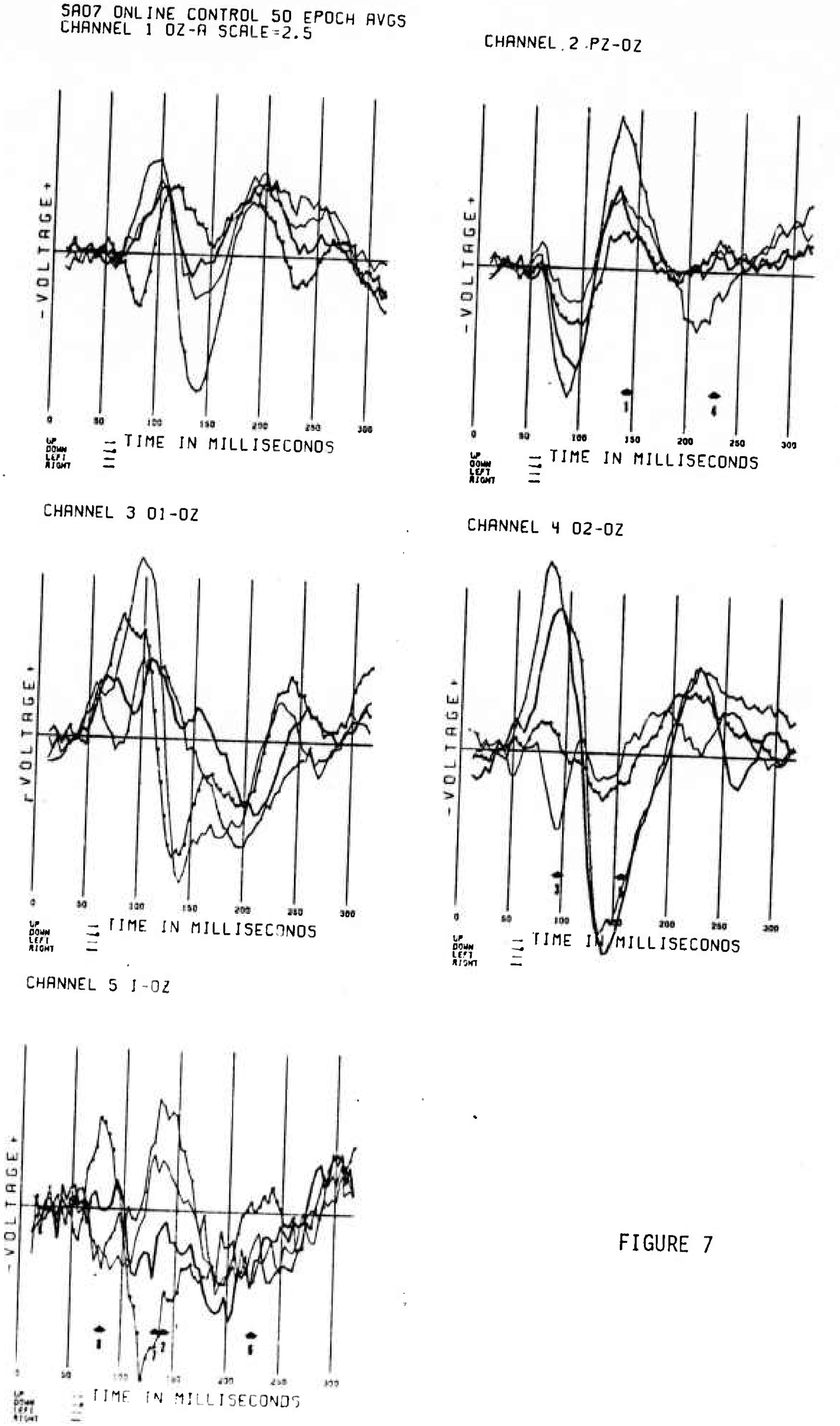
Figures 7 to 17 present averaged evoked responses to the four command stimuli. Each figure includes the averages for all 5 channels of data taken from one subject. The baselines have been corrected by subtracting the average of the samples 4 through 10 from each of the samples. The first 3 samples in each epoch have been deleted.

Full scale peak to peak amplitude is 16 microvolts for those plots with a scale factor of 2.5, and 8 microvolts for those with a scale factor of 5.0. The flash occurred at t=0.

The arrows mark the best 6 samples found by the stepwise discriminant analysis program based on a training set consisting of the first 96 epochs in the data set. They are numbered according to the rank of their F levels; the sample with the highest F level is numbered 1.

Subject SA07, Figure 7, is marked with the best 8 samples selected.

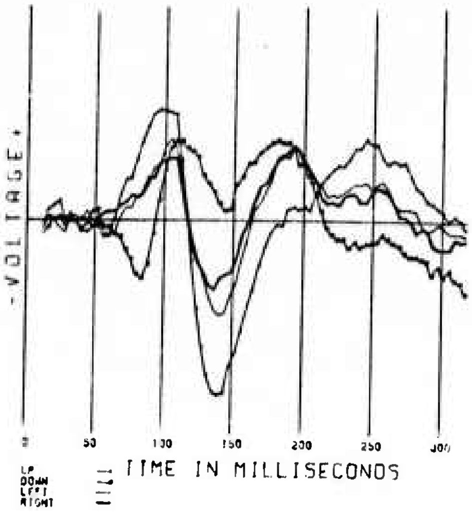
7·H



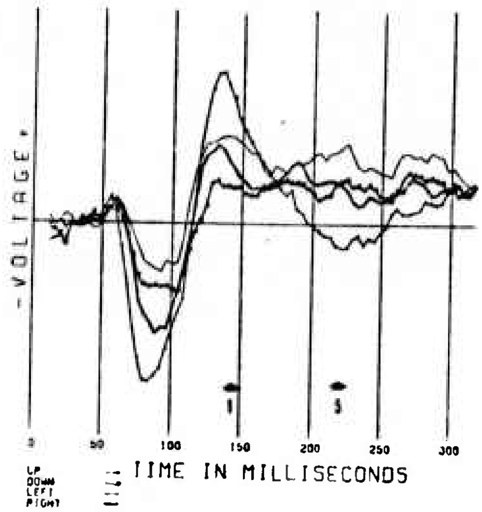
SA07 ONLINE CONTROL 50 EPOCH AVGS
CHANNEL 1 OZ-A SCALE=2.5
-VOLTAGE+
0 50 100 150 200 250 300
TIME IN MILLISECONDS
UP
DOWN
LEFT
RIGHT
CHANNEL 2 PZ-OZ
-VOLTAGE+
0 50 100 150 200 250 300
TIME IN MILLISECONDS
CHANNEL 3 O1-OZ
-VOLTAGE+
0 50 100 150 200 250 300
TIME IN MILLISECONDS
CHANNEL 4 O2-OZ
-VOLTAGE+
0 50 100 150 200 250 300
TIME IN MILLISECONDS
CHANNEL 5 I-OZ
-VOLTAGE+
TIME IN MILLISECONDS

FIGURE 7

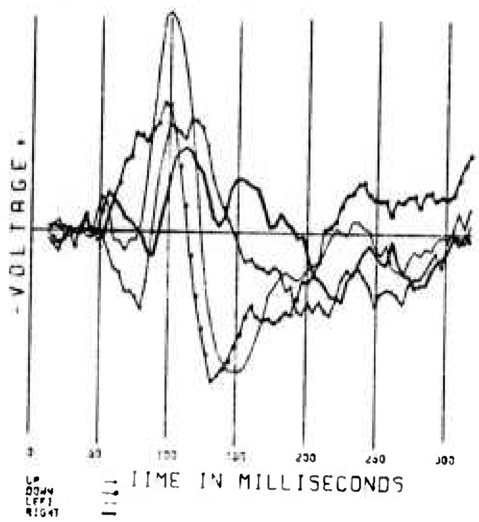
SA06 ONLINE CONTROL 50 EPOCH AVGS
CHANNEL 1 OZ-A SCALE=-2.5



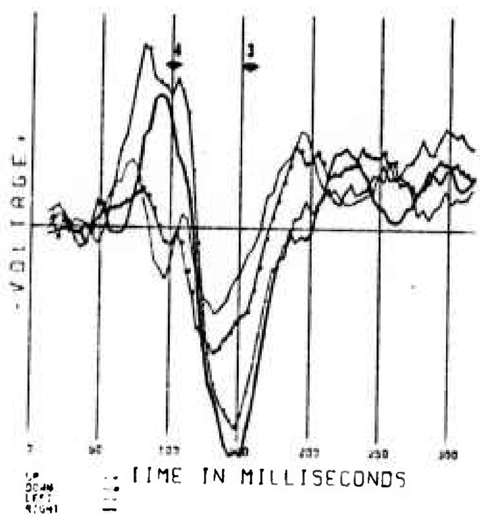
CHANNEL 2 PZ-OZ



CHANNEL 3 01-0Z



CHANNEL 4 02-0Z



CHANNEL 5 T-0Z

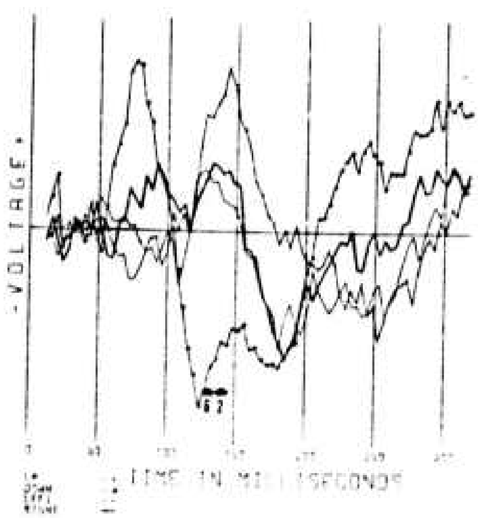
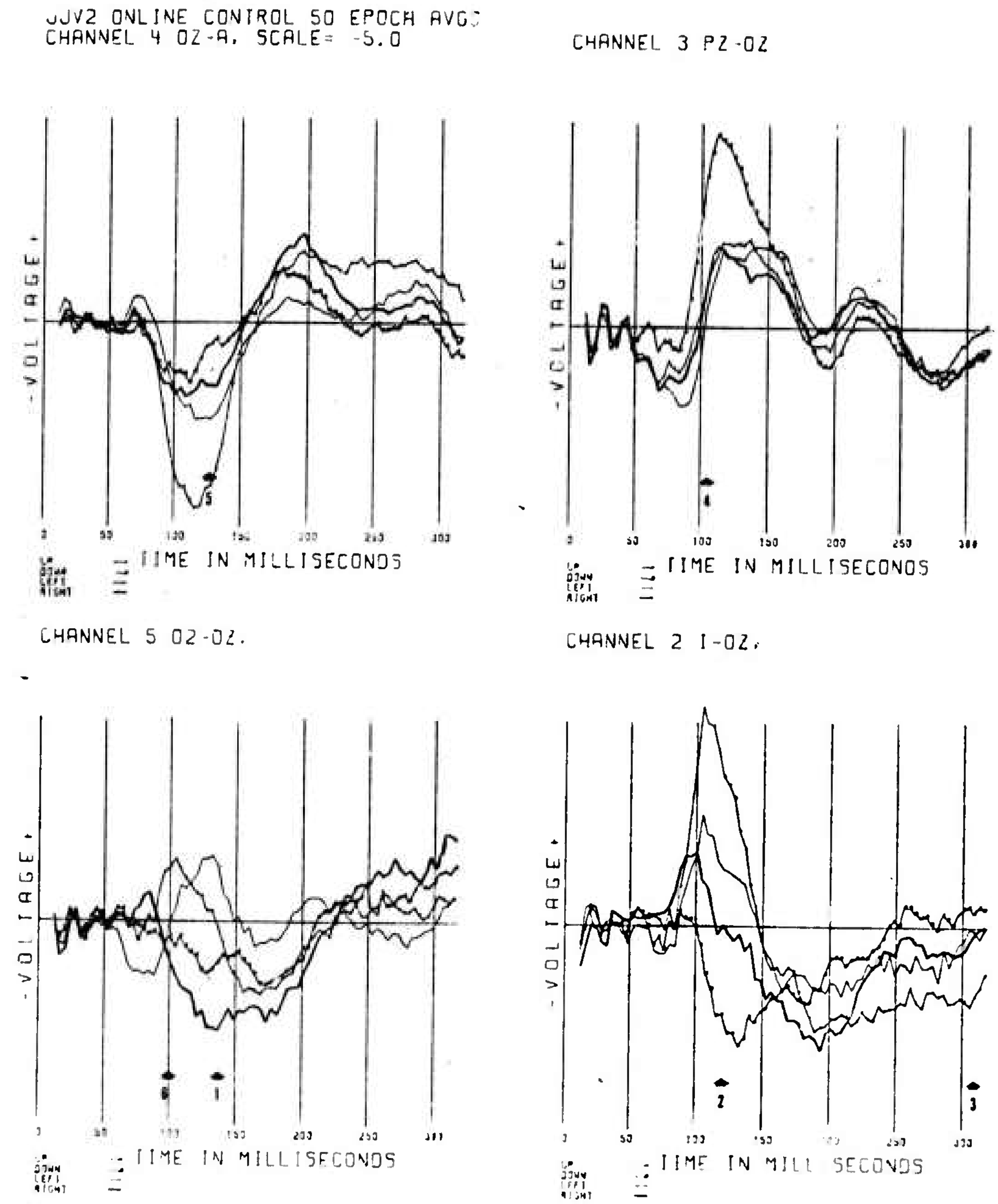


FIGURE 8

70-d



JJV2 ONLINE CONTROL 50 EPOCH AVG
CHANNEL 4 OZ-A, SCALE= -5.0
CHANNEL 3 PZ-OZ
CHANNEL 5 O2-OZ
CHANNEL 2 I-OZ
- VOLTAGE +
TIME IN MILLISECONDS
UP
DOWN
LEFT
RIGHT
0
50
100
150
200
250
300

FIGURE 9

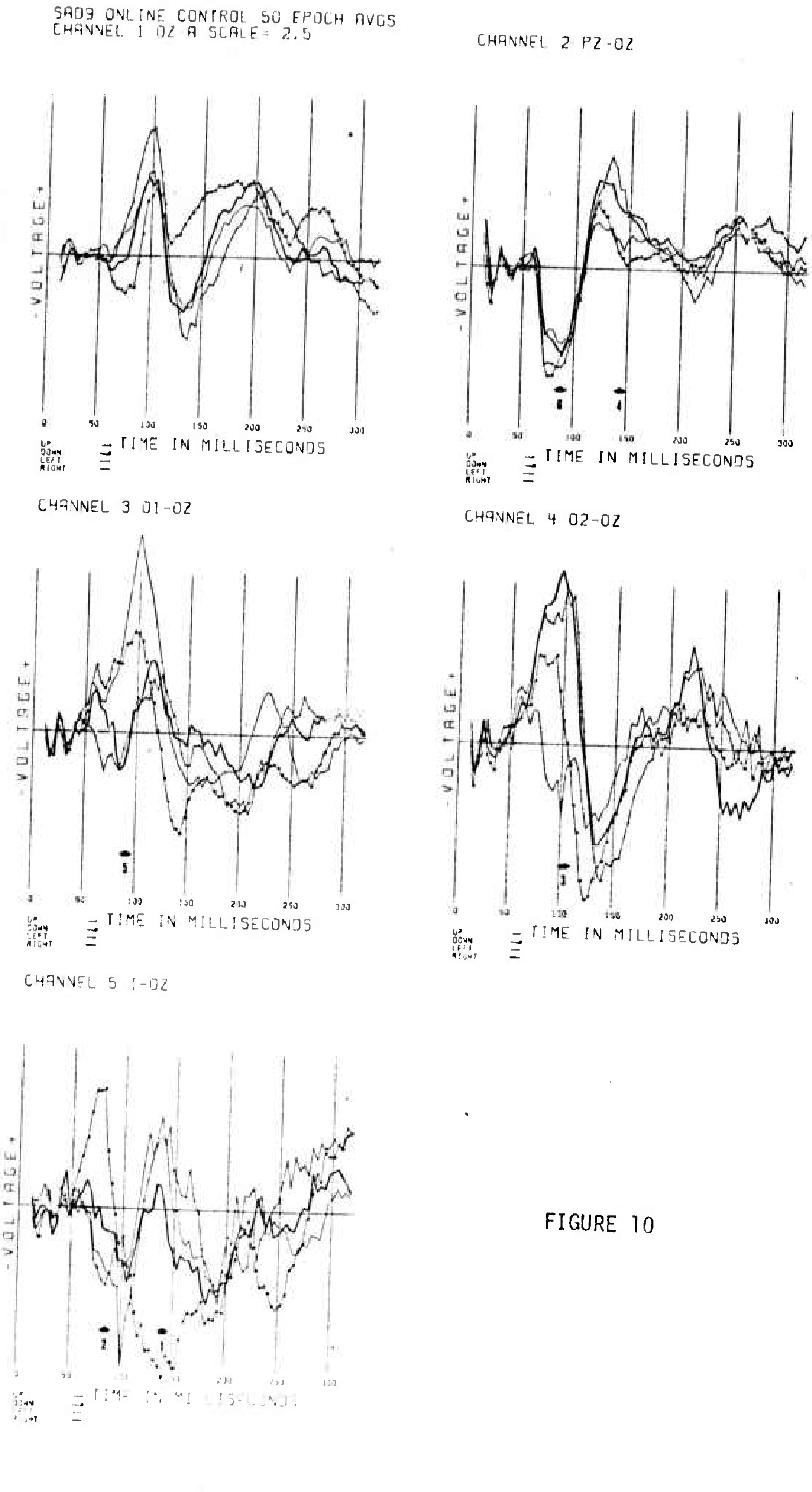

SAD9 ONLINE CONTROL 50 EPOCH AVGS
CHANNEL 1 OZ-A SCALE= 2.5
CHANNEL 2 PZ-OZ
CHANNEL 3 O1-OZ
CHANNEL 4 O2-OZ
CHANNEL 5 !-OZ
-VOLTAGE+
0
50
100
150
200
250
300
TIME IN MILLISECONDS
UP
DOWN
LEFT
RIGHT

FIGURE 10

70 L

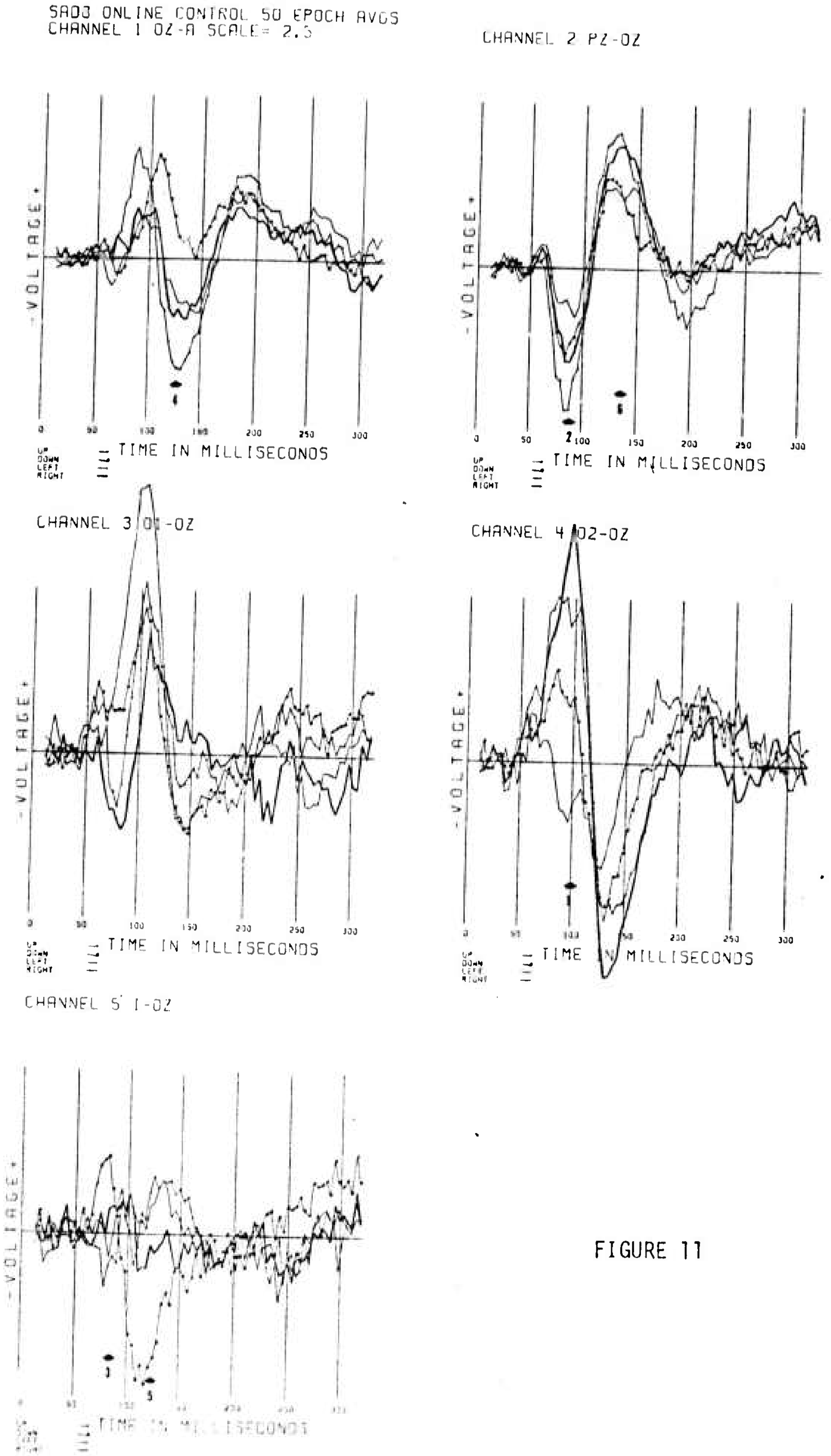


FIGURE 11

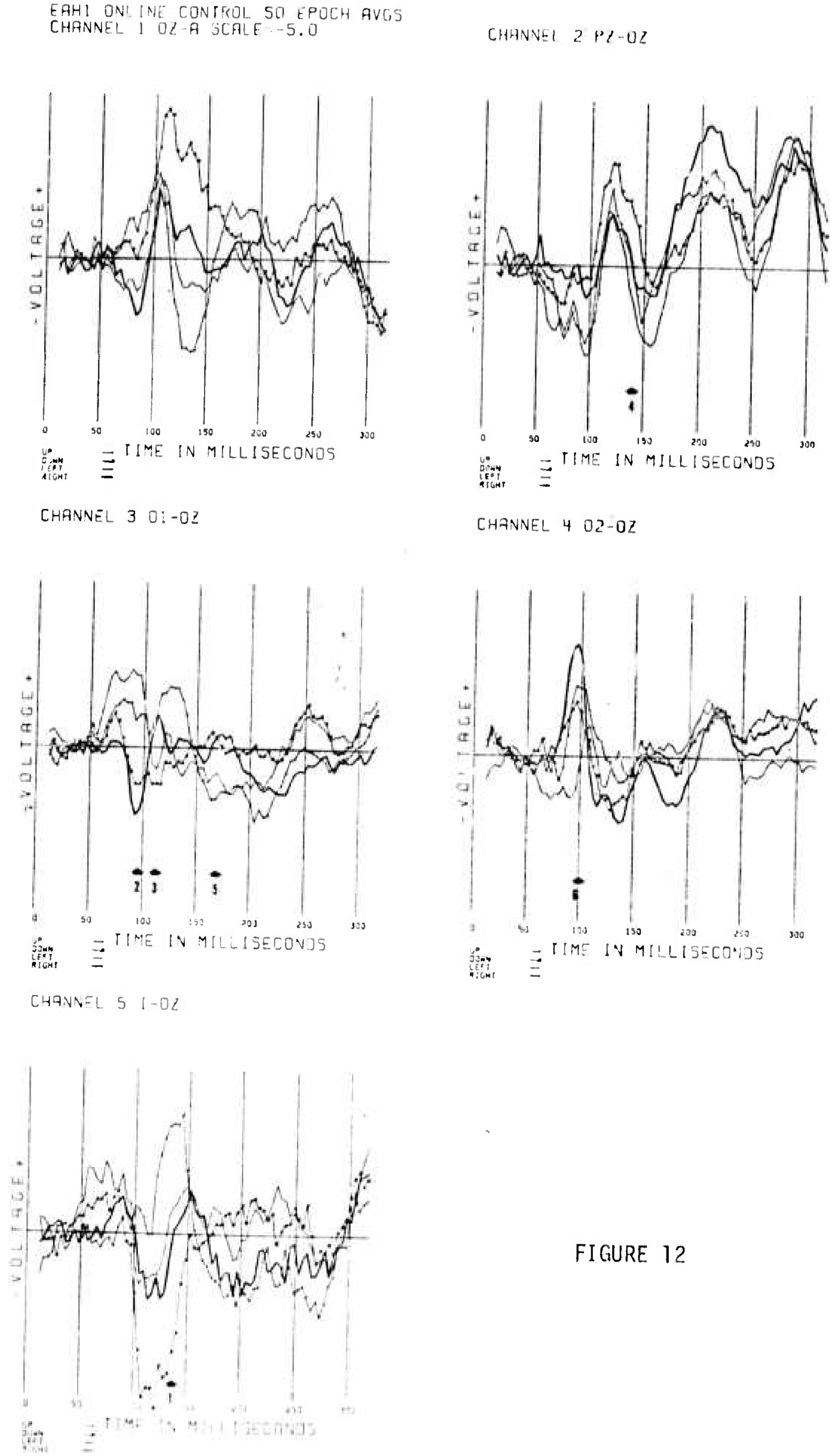

EAHI ONLINE CONTROL 50 EPOCH AVGS
CHANNEL 1 OZ-A SCALE--5.0
CHANNEL 2 PZ-OZ
CHANNEL 3 O1-OZ
CHANNEL 4 O2-OZ
CHANNEL 5 I-OZ
-VOLTAGE+
TIME IN MILLISECONDS
UP
DOWN
LEFT
RIGHT
0
50
100
150
200
250
300

FIGURE 12

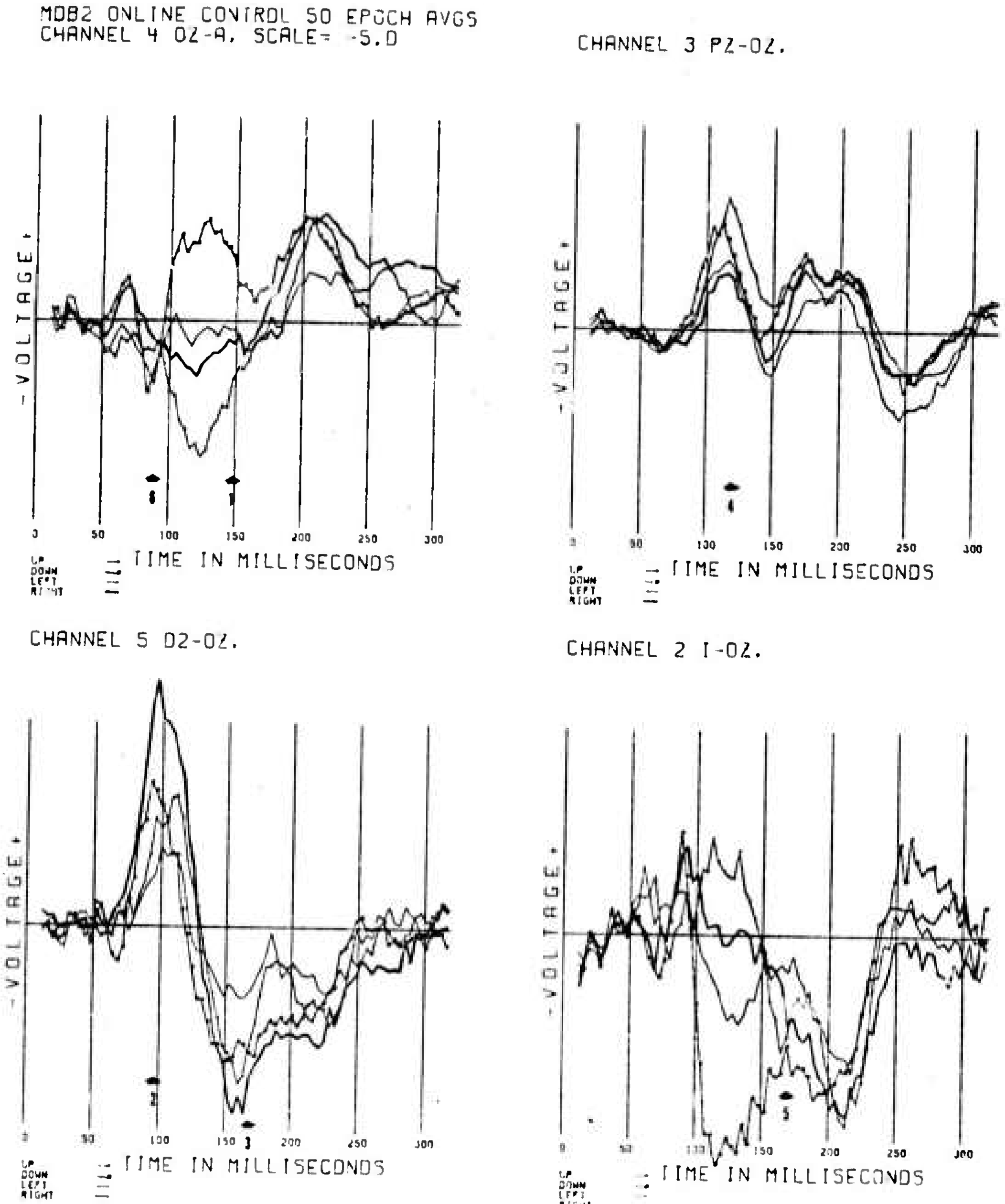
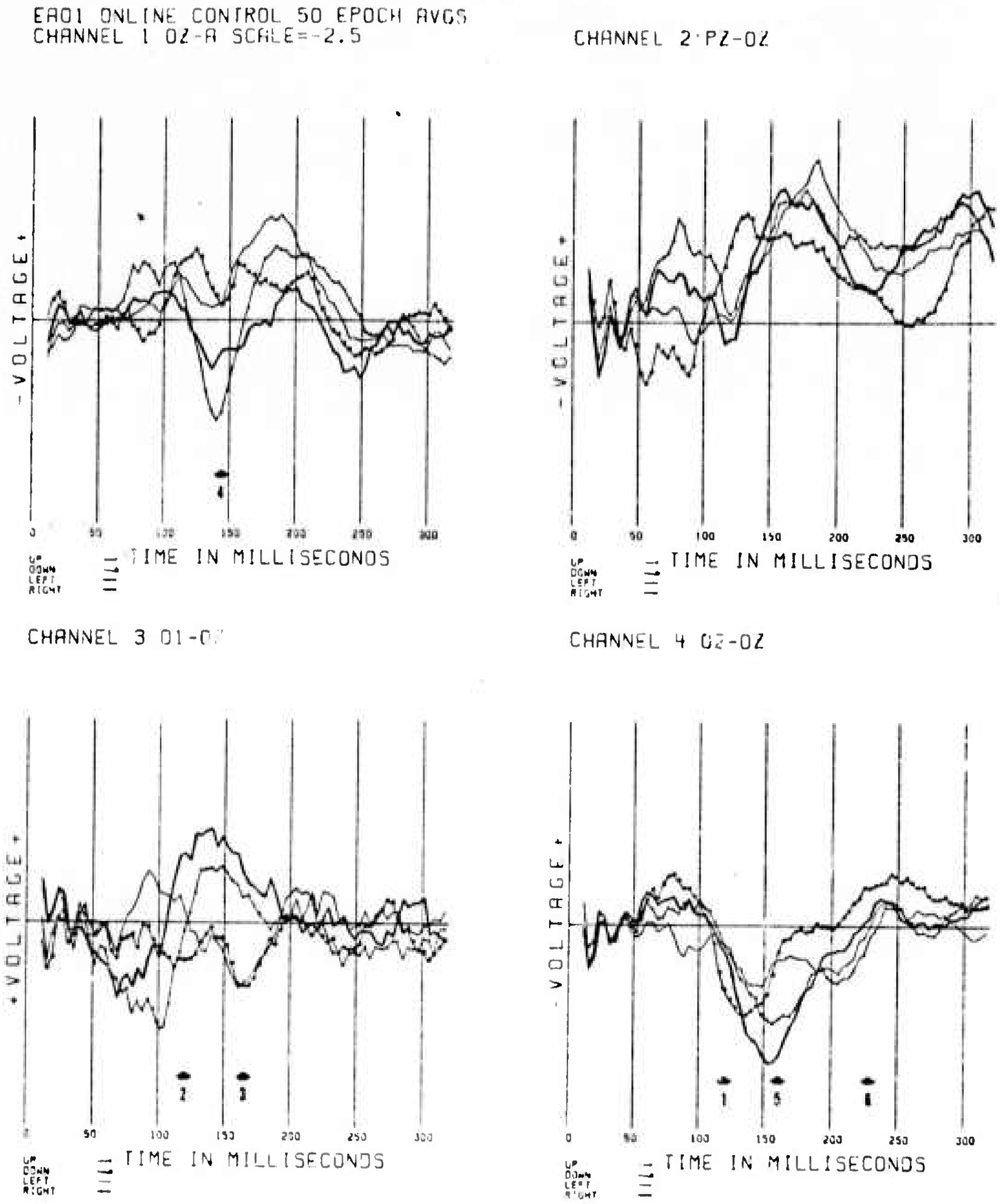

MDB2 ONLINE CONTROL 50 EPOCH AVGS
CHANNEL 4 OZ-A, SCALE= -5.0
CHANNEL 3 PZ-OZ.
CHANNEL 5 O2-OZ.
CHANNEL 2 I-OZ.
-VOLTAGE+
0 50 100 150 200 250 300
TIME IN MILLISECONDS
UP
DOWN
LEFT
RIGHT

FIGURE 13

70 0



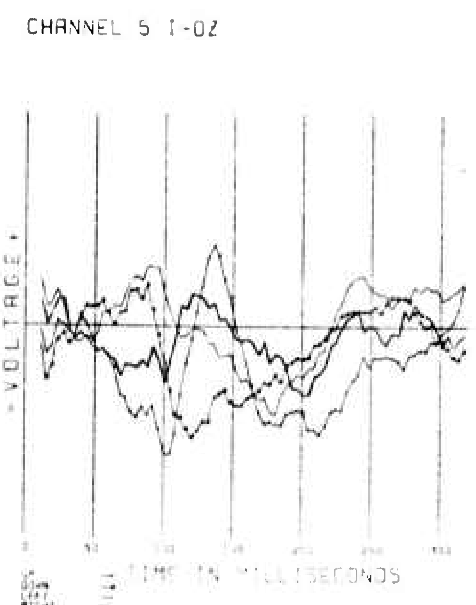
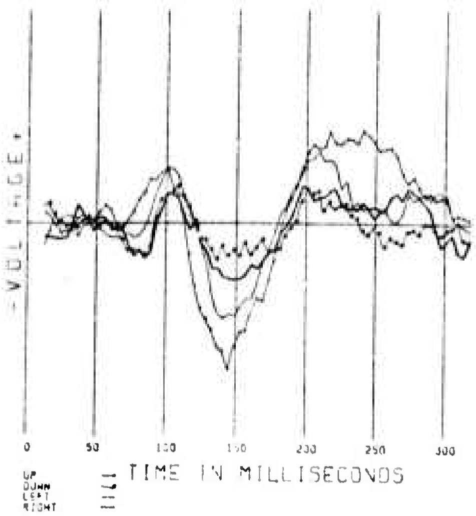


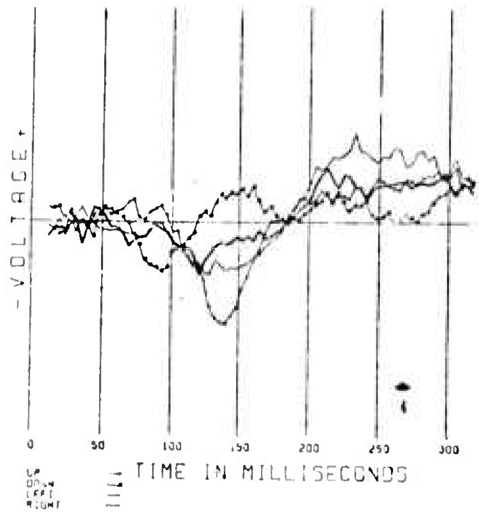
FIGURE 14

70 P

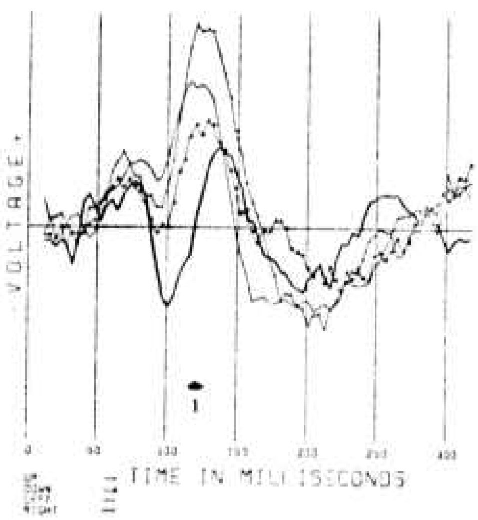
SAG4 ONLINE CONTROL 50 EPOCH AVGS
CHANNEL 1 OZ-A SCALE= 2.5



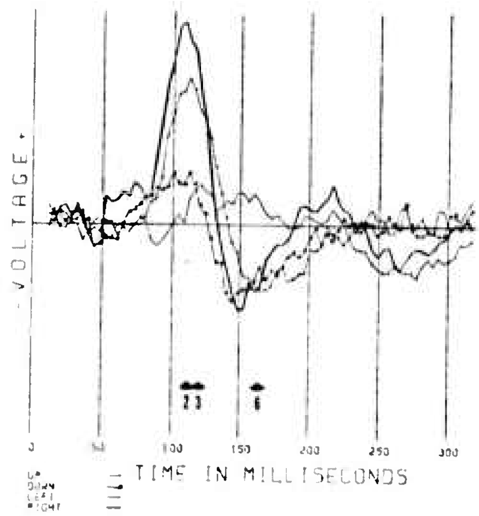
CHANNEL 2 PZ-OZ



CHANNEL 3 O1-OZ



CHANNEL 4 O2-OZ



CHANNEL 5 I-OZ

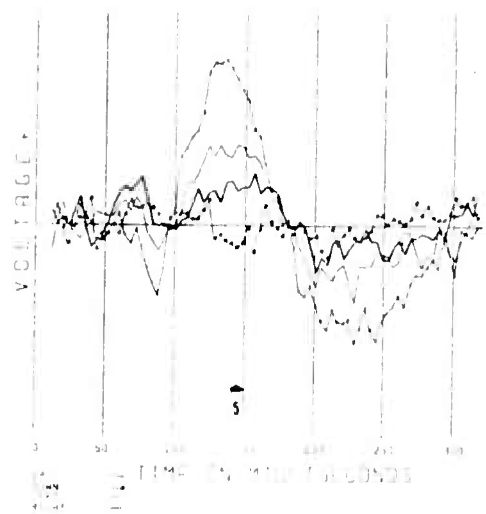
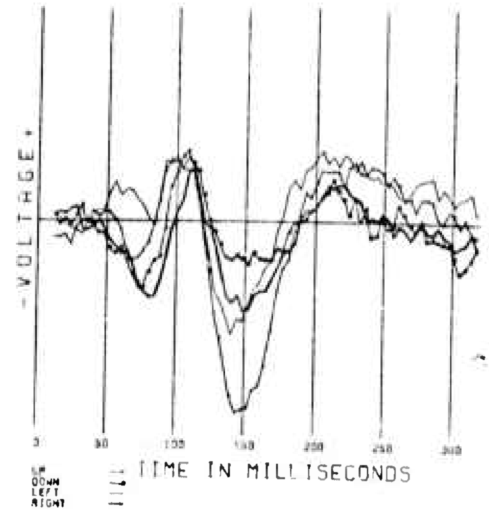


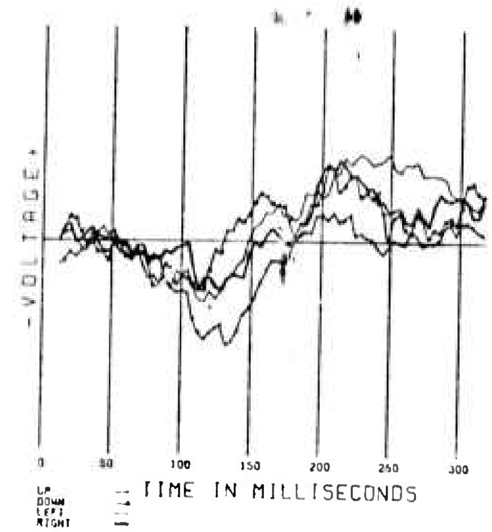
FIGURE 15

SAG3 ONLINE CONTROL 50 EPOCH AVGS

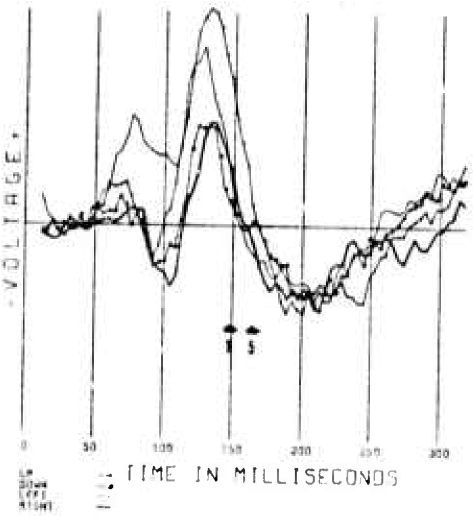
CHANNEL 1 OZ-A SCALE=-2.5



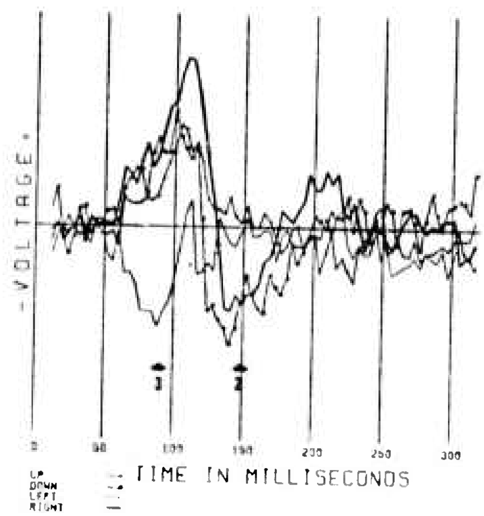
CHANNEL 2 PZ-OZ



CHANNEL 3 O1-OZ



CHANNEL 4 O2-OZ



CHANNEL 5 T-OZ

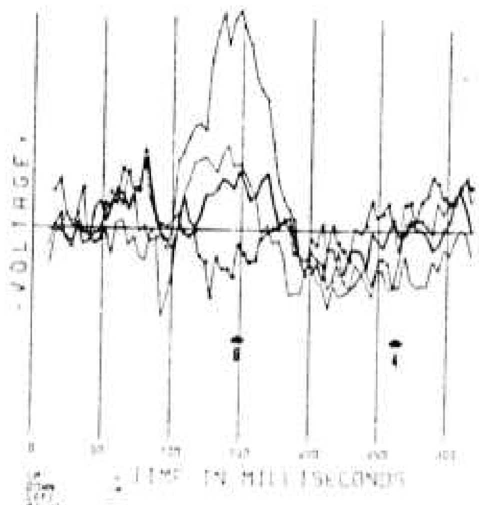


FIGURE 16

70-R

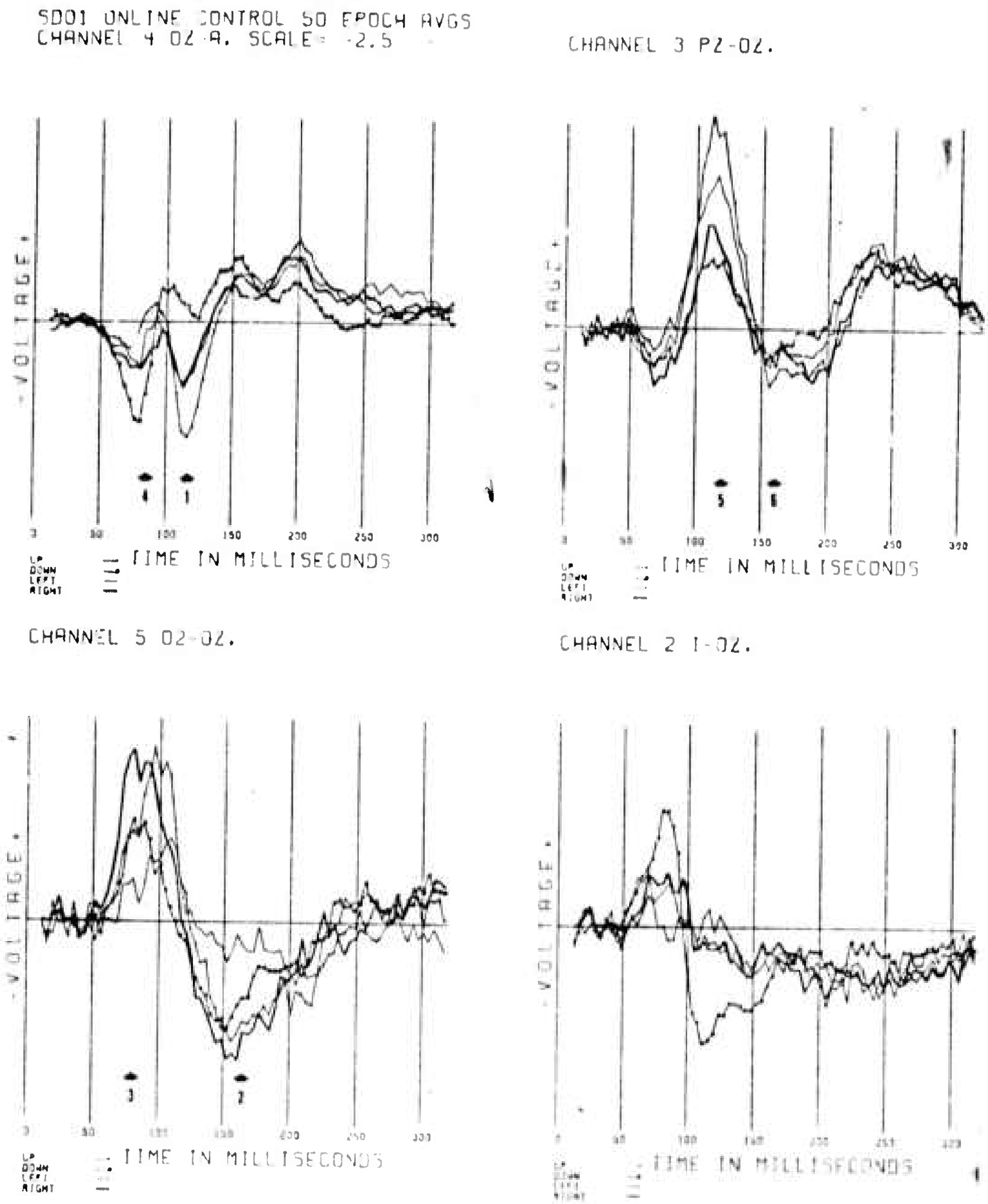


FIGURE 17

5. FACILITIES

The project will continue to be conducted under the auspices of the Computer Science Department, University of California, Los Angeles. The principal facility for this project is the computer system at the Brain Computer Interface Laboratory. Laboratory equipment includes three dedicated computers (XDS 930, XDS 920 and IMLAC PDS-1) with complete peripherals (card readers, card punch, rapid access drum, tape drives and line printer.

Experiment subjects are monitored from a specially designed shielded enclosure that contains various input devices and output displays designed in a modular fashion for ease of interfacing with the digital system. The experiment is conducted from an adjacent room containing the control terminals to the system computers, the recording equipment for EEG and other biosignals, as well as voice and video communication devices. The amplified EEG signals are routed to a digitizing station capable of handling 50 simulteneous channels of analog input. During experiments, a dedicated XDS 930 computer with 16K words of core memory and 2M characters on magnetic drum acts as data input controller and real-time experiment controller. All real-time processing functions are performed by the 930 which also creates complete experiment records for off-line batch processing. These contain, for each data "epoch," the experiment parameters (sampling rate, epoch lengths, etc.) specified by the experimenter as well as selected results of on-line computation, subject responses, etc. The 930 also controls an IMLAC PDS-1 minicomputer and display terminal with 8K of memory which is reserved for the generation of visual feedback displays for the subject (MASTER) and information for the experimenter. In addition, the PDS-1 as a stand-alone computer can perform extensive calculations and generate sophisticated graphics including animation.

For very large data processing programs, the main computing power is provided by the campus IBM 360/91 (Campus Computing Network) which is equipped with a large core memory of 4M bytes. The digitized data reaches the IBM 360/91 from the laboratory by a special hard wired, dedicated data line that is used to write and read efficiently into and from the 360/91 core. The data transfer is controlled with a separate processor (XDS 920) which has recently been replaced with a 16K interlaced version to allow buffering and transfer without interference with experiments. A monitor program in the 360/91 controls both the data flow and the processing protocol from a privileged position with respect to the 360/91 operating system software, thus insuring immediate execution. Complex data analysis can be performed and the results fed back to the laboratory with minimum turnaround time. The "awakening" of this software system and all subsequent file handling are placed under the campus timeshared system (URSA) and controlled by an IBM 3277 terminal in the laboratory.

Finally, the BCI laboratory computer system has wired-in direct access to the ARPA Network. The network is being used for accessing and transmitting data to other facilities (e.g., UCLA-ATS, CCN, MIT-MULTICS, BBN and LBL.) and for communication with other research groups.

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